Does Oil (exergy) Efficiency Matter?

US and Japanese case studies

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I would like to dedicate this thesis to inspiring feats of human endurance.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 10300 words including footnotes and equations but excluding appendices, bibliography, tables and graph legends and has fewer than 48 figures and 11 tables.

Olga Carvalho
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Abstract

Nowadays New-Keynesian Dynamic Stochastic General Equilibrium (DSGE) models have been widely used by Central Banks for long-term forecast purposes. Contrary to General Equilibrium models (GEM) these are dynamic and stochastic models that assume a variety of market failures such as wages and prices stickiness. Based in two versions of a two-country DSGE model already published by Bodenstein and Guerrieri (2012) our main purpose is to explore how changes in home (and foreign) oil efficiency, modeled as factor-augmenting technology, can influence oil prices and economic growth in the U.S. and Japan over the last four decades. Notwithstanding we apply a bayesian estimation approach instead of Bodenstein and Guerrieri (2012)'s full information maximum likelihood method. We also add seven separate sources of exogenous shocks, to the original fifteen, as we impose all autoregressive coefficients to be different for shocks that equally occur at home and in the foreign bloc. The focus of our research relies on the shock decomposition analysis of several endogenous variables such as oil prices and oil consumption, wage and core inflation, interest rates and GDP growth by paying a special attention to the post-world war II technology, oil supply and oil efficiency shocks. In agreement with Ayres and Warr (2005) we don't find, after the 70s, that historical improvements in exergy conversion-to-work efficiency explains almost entirely the Solow residual (technological progress) of the U.S. and Japan since a non negligible contribution of home (and foreign) technology shocks to the GDP growth is recorded. Notwithstanding, we observe a significant impact of oil efficiency shocks on oil consumption, oil prices, GDP growth and remaining endogenous variables. Moreover we were able to identify all the post-WWII oil supply disruptions through a reduced positive impact of world oil supply shocks in oil prices. The impact, however, passed more unnoticed in the shock decomposition plot of Japan's economy, due to higher magnitudes of home (and foreign) oil efficiency shocks, which reinforces the idea preconised by Ohtsu and Imanari (2002) that the early transformation of Japan from an energy-consuming economy to an energy-conserving one may have played an important role on the minor exposition of the Japanese's economy to post-world war II oil supply disruptions. The reliability of the previous observation is attested, in both economies, by the respective projection of crude oil and petroleum products exergy efficiencies computed by Warr et al. (2010) in the impact of

oil efficiency shocks on oil consumption. Futhermore, the rise of macroeconomic stability and less frequent oil shocks, appointed by Nakov and Pescatori (2009) as an explanation of the "Great Moderation", were also patent in both oil price shock decompositions after the middle 80s.

Keywords: Economic Growth, New-Keynesian Dynamic General Equilibrium Models, Bayesian Estimation, Exergy Efficiency

Resumo

Os novos modelos keynesianos estocásticos de equilíbrio geral (DSGE) têm sido recorridamente utilizados, em nossos dias, por Bancos Centrais para fins de previsão económica de longo prazo. Contráriamente aos modelos de equilíbrio geral (GEM) estes são modelos dinâmicos e estocásticos que assumem diversas falhas de mercado, nomeadamente, associadas à rigidez salarial e de preços. Tendo em conta duas versões de um modelo DSGE, para dois países, recentemente publicado por Bodenstein and Guerrieri (2012), a proposta deste trabalho pretende explorar o impacto das alterações de eficiência energética das últimas quatro décadas, incorporadas no modelo como fonte de progresso técnico, no preços do petróleo e crescimento económico dos Estados Unidos e Japão. No entanto, introduzimos algumas alterações ao modelo base, momeadamente, estimamos os parâmetros pelo método bayesiano em detrimento do método da máxima verossimillança utilizado por Bodenstein and Guerrieri (2012). Adicionamos sete choques exógenos, aos quize iniciais, uma vez que estimamos valores diferentes para os coeficientes autorregressivos dos choques que ocorrem em ambos os países. O foco do nosso trabalho esse recai na análise da decomposiçao dos choques repeitante a várias variáveis endógenas, nomeadamente, preços e consumo do petróleo, inflação dos salários e preços, taxas de juro e crescimento do PIB, outorgando uma atenção cuidada aos choques tecnológicos, do lado da oferta do petróleo e da eficiência energética. Em acordo com Ayres and Warr (2005) os nossos resultados demonstram que, após os anos 70, os ganhos históricos de eficiência associados à conversão da exergia em trabalho não explicam substancialmente o resíduo de Solow (progresso técnico) das economias dos Estados Unidos e Japão, uma vez que o impacto de choques tecnológicos no crescimento do PIB é significativo. Todavia, o impacto dos choques associados à eficiência energética no preço e consumo do petróleo, crescimento do PIB e demais variáveis nao é menos desprezível. Adicionalmente identificamos todos os choques petrolíferos do pós segunda guerra mundial pela observação de choques do lado da oferta do petróleo que instigaram um ligeiro impacto no aumento do preço do petróleo. Eficiências energéticas mais elevadas no Japão atenenuaram, porém, a visualização desse impacto na respectiva economia quando comparado com o efeito observado na economia dos Estados Unidos. Esta observação reinforça a ideia preconizada por Ohtsu and Imanari (2002) de que a precoce transformação do Japão, sob o ponto de vista energético, de uma economia de consumo para uma economia de conservação, pode ter contribuído significativamente para a menor exposição da economia Japonesa aos choques do lado da oferta do petróleo ocorridos após a segunda guerra mundial. O grau de confiança destes resultados é reforçado, em ambas as economias, pela projeção das eficiências exergéticas do crude e petróleo, calculadas por Warr et al. (2010), no impacto dos choques associados à eficiência energética no consumo do petróleo. Adicionalmente observamos uma crescente estabilidade nas diversas variáveis macroeconómicas, bem como, uma diminuição da frequência dos choques petrolíferos, a partir de meados da década de 80, apontadas por Nakov and Pescatori (2009) como possíveis explicações da "Grande Moderação".

Resumo: Crescimento Económico, Novos Modelos Keynesianos Estocásticos de Equilíbrio Geral, Método Bayesiano, Eficiência Exergética

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Chapter 1

Introduction

Traditionally there are four major types of energy analysis models, macro-economic models, energy systems planning models, energy systems balancing models, grid operation and dispatch models (Pina, 2012) where one of the two mainly designs, the bottom-up and top-down approach (Crespi et al., 2008), is applied. In what concerns energy models the bottom-up methodology, e.g. Grubler and Messner (1998), typically considers induced technological change in a learning-by-doing framework, in which the costs of various technologies decrease with experience. On the other side endogenous technological change in top-down models typically comes through accumulated investment in research and development (R&D) (e.g. Popp (2004), Smulders and Nooij (2003)). Usually, macro-economic models are the product of a top-down approach design although the combination of both approaches has also been applied in recent years (Proença, 2013).

Nowadays New-Keynesian Dynamic Stochastic General Equilibrium (DSGE) models have been widely used by Central Banks for long-term forecast. Contrary to General Equilibrium Models (GEM) these are dynamic and stochastic models that assume a variety of market failures such as wages, price stickiness and have been found to be very useful in analyzing the effects of structural changes in the economy, as well as the effects of longer-term developments such as persistent fiscal deficits and current account deficits. The application of several estimation procedures into DSGE models, inter alia the Bayesian method, is also possible (An and Schorfheide, 2007a; Ruge-Murcia, 2007). Accordingly to Lubik and Schorfheide (2005) an advantage of the Bayesian approach is that prior distributions can play an important role through information that added to the estimation sample helps to sharpen inference.

Lately DSGE empirical literature has also been applied into the study of oil supply shocks. If exogenous oil prices were earlier discussed (Leduc and Sill, 2004), (Leduc and Sill, 2005) and accredit (Hamilton, 2003), nowadays, based on empirical evidence (Barsky and Kilian, 2001, 2004; Hamilton, 2003; Kilian, 2008a) and some modeling optimizing first principles for oil supply (Nakov and Pescatori, 2009), the emphasis relies on the assumption of endogenous oil prices. Subsequently, DSGE models endogenizing oil prices have been already explored by few authors. If, beyond oil prices, Stevens (2013) endogenized oil production and treated oil as a storable commodity Bodenstein and Guerrieri (2012) opted by an exogenous oil supply mechanism. Noteworthily is that oil efficiency has been remarkable modelled as a factor-augmenting technology by the later author. It allowed him the construction measures of oil efficiency for aggregate (and individual) foreign countries, based on the growth-accounting studies of Solow (1957) and Griliches and Jorgenson (1966).

The logic behind this procedure seems to be in accordance with Ayres and Warr (2005)'s accounting for growth. This author demonstrated that much of the unexplained Solow residual (technological progress) of the U.S. over the last century was almost entirely explained by historical improvements in exergy conversion-to-work efficiency. Ever since, aggregate exergy efficiencies of the last decades for a couple of countries have been published by Warr et al. (2010), Willians et al. (2008), Serrenho et al. (2014), Serrenho et al. (2013), Brockway et al. (2014), Brockway et al. (2015) and Guevara et al. (2014). Although Ayres and Warr (2005)'s results seems of most importance they were computed with a formal model (Resource-Exergy Service or REXS). Taking into consideration the aggregate exergy conversion-to-work efficiencies published, more recently, by Warr et al. (2010) and Brockway et al. (2014) and the Bodenstein and Guerrieri (2012)'s DSGE model our purpose is to explore (and compare) the historical aggregate exergy conversion-to-work efficiencies relation with technological progress, appointed by Ayres and Warr (2005), in the U.S. and Japan. Additionally, explore if there is some connexion between trends in exergy conversion-to-work efficiencies and the economic reactions of these economies to the Post-World war II oil supply disruptions (Hamilton, 2011).

The dissertation proceeds as follows. In the following chapter we continue with a state of the art literature review of new-keynesian (DSGE) models moving forward with a main characterization of the Post-World War II oil supply disruptions (and their impact in U.S. and Japan economic growth) and with an introduction to exergy efficiency as a proxy of technological progress. The overall research proposal is addressed in the initial part of the third chapter. The chapter carries on with a detailed description of the applied methodology, namely, the model structure, the bayesian approach and the priors distributions of our estimates. The results are exclusively allocated to the fourth chapter. It is worthy to refer the identification and sensibility analysis of the estimated parameters and the historical shock decomposition of several endogenous variables, namely, oil prices and oil consumption, wage and core inflation, interest rates and GDP growth. Moreover, a comparison analysis between the stochastic processes of home (and foreign) oil efficiencies associated to oil consumption and the crude oil exergy efficiencies computed by Warr et al. (2010) is present at the end of the chapter. Some conclusions and final remarks are addressed in chapter five.

Chapter 2

Fundamental Concepts

2.1 New-Keynesian (DSGE) models

The phylactery of modern macroeconomics are DSGE models. These macroeconomic models have literally revolutionized their GEM predecessors by embodying powerful simulation techniques and novel solution algorithms into a previous GEM micro-foundation structure, nowadays characterized by a higher complex combination of parameter values. With an increasing model complexity the main concern was transferred to the assessment of the robustness of the results. Once more novel solutions and powerful simulation techniques proved important not only for the estimation procedures but also for the construction of toolboxes that allowed sensitivity analysis of the model's parameter set. Nevertheless, even sophisticated maximization algorithms run into serious difficulties when maximizing the likelihoods of these dynamic models. Consequently, the standard errors of the estimates were notoriously difficult to compute. Fortunately, an easy way to explore the likelihood arised with Markov chain Monte Carlo (McMc) methods (Villaverde, 2010) often associated with an estimation Bayesian approach (An and Schorfheide, 2007a; Ruge-Murcia, 2007).

Detrending and elimination of outliers from observed data (Canova (2007); DeJong and Dave (2007) in Tovar (2008)) and the determination of an approximated solution of the economic system through a first (second or third) order Taylor approximation around the steady state (Villaverde, 2010) are common prerequisites of DSGE models which may, in fact, triggered a couple of caveats meticulously appointed by Tovar (2008). Nonetheless, DSGE models have been hugely applied in forecasting, story-telling, and policy experiments purposes (Negro and Schorfheide, 2012) due to a demarcated dynamic and stochastic shocks. They encompass a broad class of standard neoclassical macroeconomic models (Negro and Schorfheide, 1988) and new keynesian monetary models (Christiano et al., 2005; Smets and Wouters, 2003) that combined rational expectations (derived from assumptions about preferences, technologies) with staggered price and wage setting, and policy rules (Schmidt and Wieland, 2013).

Forward-looking and optimizing behavior of households and firms were added elements into these models in the late 1970s, through an attemp to satisfactorily explain the 1970s stagflation raised (Schmidt and Wieland, 2013). Nominal rigidities (Calvo, 1983; Fisher, 1977; Taylor, 1980) and new methods for solving linear and nonlinear dynamic models with rational expectations as estimation procedures supported on maximum likelihood techniques (Fair and Taylor (1983); Hansen and Sargent (1980)) were incremented in the 1980s. Interesting examples of this first-generation of new keynesian models are Adolfson et al. (2007), Coenen et al. (2008) and Christoffel et al. (2010) , and Edge et al. (2009) in Negro and Schorfheide (2012). A second generation is represented by monetary business cycle models. They were firstly published by Goodfriend and King (1997) and Rotemberg and Woodford (1997) in the late 1990s. This new keynesian-style macroeconomic modeling conjugate the previous nominal rigidities and imperfect competition with a new microeconomic foundation approach (Plosser, 1989) practiced in Real Business Cicle (RBC) literature (Kydland and Prescott, 1982) that put technological innovations forth as main drivers of business cycles.

An explosion in new keynesian modeling has been witnessed ever since. Noteworthily are Christiano et al. (2005), Smets and Wouters (2003) and Smets and Wouters (2007) models. Christiano et al. (2005) was the first to show that an optimization-based model with nominal and real rigidities (such as habit persistence in consumption, adjustment cost of investment or a changing utilization rate of capital) could account successfully for the effects of a monetary policy shock (Villaverde, 2010). The work of Smets and Wouters (2003) on its side demonstrated that New Keynesian models were able to track and forecast time series as well as, if not better than, a vector autoregression estimated with Bayesian techniques (BVAR) (Tovar, 2008). Meanwhile bayesian estimation procedures have been increasingly adopted in DSGE models (An and Schorfheide, 2007a; Ruge-Murcia, 2007) by adding information to prior distributions that helps to sharpen inference (Lubik and Schorfheide, 2005).

2.1.1 Oil supply shocks in DSGE models

Recently DSGE empirical literature has also been applied into the study of oil supply shocks that have occurred over the last decades (Hamilton, 2011). Macroeconomic implications of oil price and supply exogenous shocks were earlier discussed by several authors, including Leduc and Sill (2004), Leduc and Sill (2005) and even accredit by Hamilton (2003). Evidences, however, have been compiled against the assumption of exogenous oil prices (Barsky and Kilian, 2001, 2004; Hamilton, 2003; Kilian, 2008a) supporting instead the notion that the oil price is affected significantly by global economic conditions. By modeling the oil sector from optimizing first principles rather than assuming an exogenous process for oil supply the previous conclusions have also been corroborated by Nakov and Pescatori (2009). In the view of these authors a shortcoming of models in which the oil price is exogenous is that macroeconomic effects and policy implications of oil price movements are independent of the fundamental cause of oil price variation.

Bodenstein et al. (2012) and Stevens (2013) were also interested in to study the best monetary policy responses to observe oil price fluctuations. The main structure of Bodenstein et al. (2012)'s model was based on a previous DSGE model design by Bodenstein and Guerrieri (2012) with an earliest purpose to study the impact of oil efficiency shocks as a driver fluctuation of oil prices. We remark, however, the exogeneity of oil production assumed by the model that accordingly to Stevens (2013) would involved perfectly inelasticity of the oil supply curve and therefore favored demand shocks in driving oil price fluctuations. Indeed, carry on with the same purpose of Bodenstein and Guerrieri (2012), Stevens (2013) constructed a DSGE model endogenizing, nonetheless, oil production and treating oil as a storable commodity. In consequence, an upward bias in the estimated contribution of oil efficiency shocks to oil price fluctuations was appointed by the author (chapter1) when he neglected speculative oil demand shocks. Notwithstanding, Bodenstein and Guerrieri (2012) 's DSGE model is remarkable by the fact that oil efficiency has been modeled as a factor-augmenting technology. It allow him the construction measures of oil efficiency for aggregate (and individual) foreign countries, based on the growth-accounting studies of Solow (1957) and Griliches and Jorgenson (1966), by taking in consideration the model estimates of the rate of trend growth in efficiency and oil price elasticity of demand.

2.2 Post-World War II oil supply disruptions

A remarkable record of post-World War II oil supply disruptions has been assembled by Hamilton (2011). In his paper the author not only meticously describes specific events that agitated the nominal oil prices of the early post-World War II era but also subsequent events compiled in what he called the age of OPEC (1973-1996) and the ones belonging to a new industrial age of oil industry (from 1997 onwards).

An attempt to identify the timing and magnitude of previous oil production shortfalls events, namely, the Yom Kippur War/Arab oil embargo (1973/74), the Iranian revolution (1978/79), the Iran-Iraq War (1980/1988), the Persian Gulf War (1990/91), the Iraq War (2003) and the civil unrest in Venezuela (2002/03) was made by Kilian (2008b) and Kilian (2008a). Several other studies also document a structural break in the oil market and the influence of oil shocks on the economy around the mid 1980s (Galí and Blanchard, 2010; Hooker, 1996, 1989; Hubbard, 1986) and nineties (Peersman and Robays, 2012).

2.2.1 The predominantly economic reaction

Accordingly to Kilian (2008a) and Flemming (1987) the predominantly economic reaction to the post-World War II oil supply disruptions is characterized by higher inflation due to net oil prices increases, proceeded by higher short-term interest rates, reduced terms of trade of manufacturing industry, low level of employment and utilization capacity which induces a fall in the real wage, a temporary reduction in real GDP growth and a depreciating currency with respect to the dollar. Notwithstanding, strong statistical evidence showed that responses to exogenous oil supply disruptions had not only differ across G7 countries (Kilian, 2008a) but also across time (Peersman and Robays, 2012). For instance, although unusually low real growths were recorded in all G7 countries for the aftermath of the 1973/74 shock and – with the exception of Japan – for the 1980 shock, three of seven countries were able to maintain average or above average real growth rates after the 1978/79 and 2002/03 shocks. In 1978/79 these countries were Italy, Germany and Japan; in 2002/03 they were the United States, the U.K. and Japan. In agreement with the previous observation Peersman and Robays (2012) suggests that a typical unfavorable oil supply shock in the nineties is characterized by a much smaller fall of world oil production and a greater effect on the price of crude oil, but a smaller impact on activity, relative to the seventies. This empirical evidence has been supported by an appointed gradual decline of the oil supply elasticities over time (Hamilton (2009); Kilian (2008a); BP, 2010) and lower price elasticity of oil demand since the mid 1980s (Cooper, 2003; Krichene, 2002; Ryan and Plourde, 2002), BP (2008). Another possibility, pointed by Nakov and Pescatori (2009), is that major oil shocks have become less frequent in the period after 1984 or that diversification towards less oil-intensive sectors and increased energy efficiency may have diminished the importance of oil shocks by reducing the share of oil in GDP. In line with the previous suggestion Peersman and Robays (2012) also appoints oil and non-oil energy intensities as an important explanation of cross-country differences over time, but after oil supply shocks only. Unexpected Kilian (2008a) demonstrates a completely different story by estimating the impact of exogenous oil supply shocks on real growth after expunging effects that precede these shocks. With his new methodology he found that in all G7 countries the 1990/91 oil supply shock caused by the Persian Gulf War contributed to somewhat reduced real growth, albeit with a considerable delay. The oil shocks of 1978/79 and 1980 also left a mark in the data of some G7 countries. In contrast, the 1973/74 oil supply shock had hardly any impact on G7 real growth. Similarly, the effect of the 2002/03 oil supply shocks was negligible for all G7 countries.

2.2.2 USA versus Japan

Despite in most countries exogenous oil supply disruptions caused at least a temporary decline in real wages, a depreciation of the local currency against the dollar and a rise in short-term interest rates there is no evidence that differences in the previous responses alone can explain the differences across countries in the inflation and output responses. As noted by Bohi (1989) [1], the striking differences in economic performance across the United States, Japan, and Germany, in particular, when faced with the same exogenous shock, are suggestive of an important role for domestic economic policies. Indeed, results for Japan point to a no short-term interest rate response and a much smaller response of Japanese real GDP growth to exogenous oil supply shocks (Kilian, 2008a). Exceptionally to other countries, U.S. included, Japanese economy absorbed the 70s second oil shock rather well as the GDP growth rate suffered only a moderate decline, from 5.2 percent in 1979 to 4.8 percent in 1980 (Kilian, 2008a; Ohtsu and Imanari, 2002). An immediate drop in real growth during late 1990 and early 1991 after the 1990 exogenous oil supply shock was also observed in U.S. but not in Japan. On the contrary both countries were able to maintain average or above average real growth rates after 2002/03 oil shocks (Kilian, 2008a).

Important channels of the transmission

Two main potentially important channels of the transmission of exogenous oil supply shocks have been appointed by Kilian (2008b). The first is based on the notion of real wage rigidities (Bruno and Sachs, 1982, 1985). A downwardly rigid real wage (as a result of pressure from labor unions) would amplify the effects of exogenous oil supply shocks on real GDP. Nonetheless, the available evidence for the U.S. suggests that more likely than not real wages fell following the oil shocks of the 1970s (Rotemberg and Woodford, 1996). Kilian (2008a) 's estimations, at no conventional significance levels, also suggest a clear evidence of falling real wages for most countries, namely, in U.S. and Japan. The second channel is an increase in short-term interest rates in response to exogenous oil supply disruptions, consistent with a monetary tightening in anticipation of future inflation (Bernanke et al., 1997). Nevertheless, contrarily to the U.S., Japanese interest rates, essentially, did not respond. Although unusually high CPI inflation rates were also observed in Japan after the shocks of 1973/74 and 1980 (Kilian, 2008a). Japanese higher CPI inflation rates, in 1980, provoked instead a downward pressure on the value of the yen and a negative rate of wages increase as the amount of trade surplus declined substantially, reflecting higher import costs of crude oil (Ohtsu and Imanari, 2002).

[1] in Kilian (2008a)

Oil price and CPI inflation

Conversely, the most recent shocks have been followed by below average inflation rates (Kilian, 2008a). The cumulative effect for the U.S. was negative (although not significantly so) and Japan experienced moderate price level increases after three years. Futhermore, U.S. oil supply disruptions tended to cause sharp spikes in CPI inflation while in Japan responses were characterized by repeat spikes. Barsky and Kilian (2004) also observed that deflator inflation responses were more muted and less significant than CPI inflation. The relationship between oil price shocks and CPI inflation is not, however, as apparent as one might have expected (Barsky and Kilian, 2004). There are serious doubt on the view that exogenous oil supply shocks are responsible for the sustained inflation of the 1970s and early 1980s. The CPI inflation attributed by Kilian (2008a) to the 1973/74, the 1978/79 and 1990 oil shocks is negligible when compared to existing levels of CPI inflation. Subsequently, the author appoints other endogenous factors such as high global demand or macroeconomic policy choices, which would help explain both the wide variation in inflation experiences across countries over the same sub period and the wide variation across different episodes in the same country (as in the case of Japan, for example). But, if the higher inflation of the 1970s and early 1980s was mainly due to macroeconomic policy choices there is no reason to invoke a monetary tightening in response to inflation caused by higher oil prices.

An alternative explanation

An alternative explanation, suggested by Ohtsu and Imanari (2002), about the minor impact of the 70s second oil crisis on the Japanese economy was that Japan, by the late 1970s, had already completed its transformation from an energy-consuming economy to an energy-conserving one. Nonetheless, apart from the studies of Bodenstein and Guerrieri (2012) and Stevens (2013) who indeed have tried to explore the connection between oil efficiencies and economic responses to exogenous oil supply shocks few literature has been published on the subject (see section 2.3).

2.3 What is exergy efficiency? A proxy measure of technical progress?

Usefull work accounting method have been pioneered by Ayres and Warr (2005). Ever since historical improvements in exergy conversion-to-work efficiency have been published for a couple of countries (Brockway et al., 2014, 2015; Guevara et al., 2014; Serrenho et al., 2014, 2013; Warr et al., 2010; Willians et al., 2008). The accounting method supported the hypothesis that energy delivered as useful work (in the thermodynamic sense) is one of the three major factors of production in modern industrialized economies. By useful work the author meant the product of resource (exergy) inputs times a conversion efficiency factor while they made a clear distinction between energy and exergy. Energy is a conserved quantity that cannot be consumed or used up but does become less able to perform useful work due to entropy. Exergy represents the fraction of total energy that is available to perform work. Additionally, efficiency is a dimensionless number between zero and unity that corresponds to the ratio of work performed to exergy supplied (Ayres, 2008). This ratio changes with (a) improvements in the efficiency of existing technologies and (b) the innovation and adoption of new technologies applied into the performance of existing process, or (c) with shifts in the structure of energy services (the type of useful work) demanded (Warr et al., 2010). For instance mechanical and electrical efficiencies tend to be significantly higher than thermal process efficiencies.

2.3.1 Global conversion efficiency improvements

On a global scale throughout the 20th century aggregate exergy conversion efficiency improvements varied by a factor of 3 to 5 (Warr et al., 2010). Exergy efficiency improved dramatically from 1950 to 1960 with the introduction of diesel (electric) rail and in the post middle 1980s with an adoption of diesel ICEs and prevalence of air travel. A dramatic global increase in steel manufacture efficiency in the early years of post-WWII was also remarked, namely, in Japanese steel making industry (Willians et al., 2008). Contrastively the "efficiency dilution" of the post 1990s reflected the quality of raw materials, pollution control mechanisms and, most significantly, of structural changes in the electricity carrier and transport sector that successively adopted less efficient technologies from an exergy perspective (Warr et al., 2010).

It seems that the first oil price shocks inflicted an overlasting change in the causal dynamics between energy consumption and economic growth. Useful work intensities peaked in the early 1970s in a couple of countries and, with few exceptions (Brockway et al., 2015; Guevara et al., 2014), displayed a temporary decline over the subsequent period to the present day (Warr et al., 2010; Willians et al., 2008). The relative decoupling of economic growth and energy use has also been intensified, in the post 1990s, due to the domestic growth of highly productive but less energy intensive service sectors (such as those reliant on ICT, as finance, (Podobnik, 2005) very often associated to a rebound effect of lower prices, demand stimulation and proliferation of economies of scale and R&D (Warr et al., 2010). Energy efficiency "rebound effect" outstripped GDP but also energy productivity losses, that coincided with (or was most certainly the cause of) a convergence in intensity measures among developed countries (Warr et al., 2010). Indeed, by 2000 the useful work intensity of GDP measured in developed countries was remarkably similar (at 1.5GJ/$1000 US), yet exergy intensity measures varied by a magnitude of 2 reflecting the characteristics of the exergy resource supply and useful work efficiency of each country (Warr et al., 2010).

U.S. and Japan efficiency and TFP

In comparison to other developed countries U.S. and Japan revealed a even more notorious S-shaped trend of efficiency improvements. Their improvements have been slower during the first half of the century and more rapid, with annual efficiency gains ranging from 2% to 4%, during post-WWII industrial reconstruction due to the introduction of state-of-the-art technologies, integrated processing and transport facilities, urbanization and electrification. Notwithstanding post 1970s efficiency gains peaked and either stagnated, with 1% annual improvements, or slowly declined to 0.5% or less since 1980 (Warr et al., 2010; Willians et al., 2008). Major investments in state-of-the-art high efficiency natural gas and oil thermal power stations, that occurred early after the WWII, able the Japanese economy to attain very high efficiencies in the late 1970s (Warr et al., 2010). Willians et al. (2008) and Warr et al. (2010) appoint towards a clear competitive advantage of Japan over U.S. in what concerns aggregate exergy efficiency (which for the authors is a reasonable proxy measure of technical progress), but more precisely on crude oil and petroleum products during the 60s, 70s and less pronounced afterwards.

From the 1970s onwards Japanese exergy inputs per unit of GDP were consistently less than half that for U.S, perhaps due to Japan's earliest complete transformation into an energy-conserving economy (Ohtsu and Imanari, 2002). Although, the fractional rate of exergy intensity yearly decline was more pronounced in US (1.53%) than in Japan (0.74%) suggesting lowest incremental improvements in energy productivity, notably in transport and the housing sector, the result of differences in spatial organization (transport distances), climatic conditions and consumer behavior (Warr et al., 2010). Surprisingly over the 70s and the 80s a higher share of environmental Patens in Japan rather than in the U.S. was accounted by Lanjouw and Mody (1996). On the other side OECD data indicates higher U.S. R&D expenditures [2] as percentage of GDP from late 70s until mid 90s.

In consonance with the Japanese energy efficiency competitive advantage hypothesis, supported by Ohtsu and Imanari (2002), Kilian (2008a) estimated a less severe reduction, among other countries, in Japanese real GDP growth after post-WWII oil supply disruptions (see 2.2.2). Technical progress, also called total factor productivity or TFP, is the part of the GDP growth that cannot be explained by factors of production (K, L, E) and is therefore

[2] Group1: energy efficiency.

considered a function of time alone. Nonetheless Ayres and Warr (2005) and Ayres (2008) found that productivity gains (TFP) for U.S. and Japan, over the past decades, are essentially explained by the use of the useful work variable in the production function which may bring a deeper insight on Kilian (2008a)'s results.

In sum, energy's accelerated demand matched GDP growth and reflected U.S. industrial development and the Japanese economic catch-up in the three decades after WWII (Warr et al., 2010). Inflated with efficiency improvements and increasing demand for exergy the aggregate work/GDP ratio of both countries rose consistently until peaking in the early 1970s just before the Arab oil embargo of 1973 (Ayres, 2008; Warr et al., 2010).

2.4 Few reflections on the State of the Art

Despite the determining role that energy (exergy) efficiency may play(ed) in the economic growth of developed economies most macroeconomists seem to have neglected its importance. To the best of our knowledge Stevens (2013) and Bodenstein and Guerrieri (2012) (and Bodenstein et al. (2012) who based its work on Bodenstein and Guerrieri (2012)'s model) are the only works that have included oil efficiency shocks into DSGE models. While Stevens (2013) sought to determine a diversity of factors that can be consider historical drivers of oil prices, Bodenstein and Guerrieri (2012) had a more specific purpose. Their aim was to estimate the contribution of oil efficiency shocks to oil prices flutuactions by capturing changes in consumption patterns or production processes. The authors modeled energy efficiency as a factor-augmenting technology. Taking into account the model's estimates of the rate of trend growth in efficiency and oil price elasticity of demand the authors also constructed measures of oil efficiency for individual foreign countries based on the approach of growth-accounting studies of Solow (1957) and Griliches and Jorgenson (1966). Bodenstein and Guerrieri (2012) found that movements in foreign oil efficiency were of principal importance in the determination of oil demand and prices over the period 1984 to 2008 both at business-cycle and longer frequencies. Whereas with his model Stevens (2013) observed an upward bias in the estimated contribution of oil efficiency shocks to oil price fluctuations if disturbances in precautionary or speculative holdings of oil inventories were neglected.

Chapter 3

Details of the Research and Methodology

3.1 Overall proposal

The main purpose of this research is to infer if Japanese energy efficiency competitive advantage justifies its better economic performance in response to the post-World War II oil supply shocks, when compared with other industrialized countries, namely, the U.S. Moreover, to explore (and compare) the historical aggregate exergy conversion-to-work efficiencies relation with technological progress (Ayres and Warr, 2005) in both countries. Japan is an interesting case study given its history of rapid economic and technological development. Over the last decades the country has, indeed, become a leading economic power in spite of an acute scarcity of domestic natural resources (Willians et al., 2008) and almost due to is superior technology. In matter of fact Japanese economic growth was considerably slower during the prewar period and significantly faster in the post-WWII era until 1992. Since then, out of line with other developed countries, namely with the U.S., its economic growth has been slowing down faster than any other (Ayres, 2008). Unsurprisingly, we believe that some empirical evidence can be find by exploring the notorious differences in the economic and technological (aggregate exergy efficiency) growth trajectories of both countries. Irrevocably Japan and U.S. economic and technological conditions seem particularly appropriated to the present research study.
The methodology applied in this study is based in two versions of a two-country DSGE model already published by Bodenstein and Guerrieri (2012). The first model, almost a replica of Bodenstein and Guerrieri (2012), allows for oil and non oil goods and encompasses U.S. and foreign trade blocs. The second, although structurally identical, is calibrated for Japan and

its correspondent foreign trade bloc [1]. We did, however, some adaptations to Bodenstein and Guerrieri (2012)'s model. Contrary to the maximum likelihood method applied by the original authors we apply the Bayesian estimation approach (An and Schorfheide, 2007b) and despite the sources of our data being slightly different from Bodenstein and Guerrieri (2012) (see annex A) we base our estimation in the same fifteen observed series (see section 3.3). Moreover, we add seven separate sources of exogenous shocks, to the original fifteen, as we impose all autoregressive coefficients to be different for shocks that equally occur at home and in the foreign bloc. The focus of our research relies on the shock decomposition analysis of several endogenous variables such as oil prices and oil consumption, wage and core inflation, interest rates and GDP growth by paying a special attention to the post-WWII technology, oil supply and oil efficiency shocks. Accordingly to Bodenstein and Guerrieri (2012) oil efficiency was modelled to measure those changes in oil demand that cannot be explained by movements in the oil price or movements in a broad measure of economic activity. Consequently, estimated values can be clearly identified through a shock decomposition analysis. Our main purpose is to provide a comparison analysis between the models' shock decomposition outputs and crude oil exergy efficiencies published by Warr et al. (2010), Brockway et al. (2014). The linearized versions of our models are solved with Dynare.

Structurally the present chapter proceeds as follows. An overview description of the model borrowed from Bodenstein and Guerrieri (2012) is stated in the first section. The second section is addressed to the observable data and to the data relation with the model-implied variables. The third section proceeds with the identification of the distributions used as priors in the implementation of the bayesian estimation.

3.2 Structural basis of the model

As already mentioned the work is based in two different versions (one for the U.S. other for the Japanese economy) of a model published by Bodenstein et al. (2012) and borrowed from Bodenstein and Guerrieri (2012). Last authors, in turn, build the model based on Backus and Crucini (1998) and Smets and Wouters (2007). Overall this is a global New-keynesian dynamic stochastic general equilibrium (DSGE) model setting with price and wage rigidities (Christiano et al., 2005; Smets and Wouters, 2007), endogenous oil prices, international trade in oil and non-oil goods (Backus and Crucini, 1998) and incomplete asset markets

[1] foreign observed variables are calculated as geometric weighted averages of individual foreign countries' observed variables. The weighting pattern is time-varying, and the most recent weights are based on trade in the 2008-10 period (see broad and narrow weights at http://www.bis.org/statistics/eer.htm)

across countries (Bodenstein et al., 2011). The model is also characterized by a symmetric country blocs (two) structure, with a continuum of firms producing differentiated varieties of an intermediate good under monopolistic competition. On the other hand the utility of households is measured with a consumption basket produced by perfectly competitive consumption. The exogeneity of the oil supply with a focus on the oil demand, that is stimulated by the consumption of households and production, are other key features. Besides the model also provides a novel decomposition of the marginal cost of production that highlights the role of each factor input for the evolution of inflation. Further, the conduct of the model monetary policy responds to an inflation term, to a lagged interest rate term and output gap. At last, instead of the 15 Bodenstein et al. (2012)'s shocks, the model encompasses an unusually rich stochastic structure with 22 separate sources of shocks, as we impose all autoregressive coefficients to be different for shocks that occur in both countries (for a comprehensive summary see Table 1 of Bodenstein et al. (2012)). A couple of these shocks were modeled following Smets and Wouters (2007), namely, shocks to investment, wage and price markups, and government spending. The relationship between current investment and its impact on the capital stock of the economy has been model to be governed by the investment-specific technology shock. Price markup shocks were modeled as raising or lowering the elasticity of substitution between product varieties. Wage markup shocks follow the same structure and affect the elasticity between differentiated labor inputs. Shocks to government spending were expressed in terms of shocks to the government spending to GDP ratio. Additionally, home and foreign technology shocks, home and foreign oil supply shocks and oil efficiency were also modeled. For a more detailed comprehension of the model's overall structure see Bodenstein and Guerrieri (2011); Bodenstein et al. (2012).

3.2.1 Balanced Growth Path

In agreement with Bodenstein and Guerrieri (2011)'s balanced growth path real quantities grow at the common rate μ_z, except for oil demand and supply, and hours worked. Prices (relative to the domestic good), including real marginal costs, are constant except for real wages and the real price of oil. With labor augmenting technological progress, hours worked are stationary and real wages need to grow with the common growth rate μ_z. Oil supply and oil demand grow at the rate $\mu_o < \mu_z$, while oil efficiency must improve over time to bridge the gap between labor augmenting technological progress and oil supply growth at the rate $\mu_{zo} < \frac{\mu_z}{\mu_o}$. Consequently, the price of oil is expected to grow at the rate μ_{zo} unconditionally (Stefanski, 2011). Nominal prices grow at the inflation rate π^*. The relationships hold along the balanced growth path for home and foreign countries are the same already defined in

Bodenstein and Guerrieri (2011). The size of the foreign bloc relative to the home country is denoted by ≥ 1 (2 for the U.S., 8 for Japan).

3.2.2 Endogenous oil efficiency

Bodenstein and Guerrieri (2011) modeled oil efficiency as a factor-augmenting technology. This methodology enables oil efficiency to be measured as those changes in oil demand that cannot be explained by movements in the oil price or movements in a broad measure of economic activity. DSGE models, through exogenous shocks, are a practical tool to easily measure this residual (i.e. growth rate of oil efficiency) throughout the estimation of the exogenous shock's parameters. Unsurprisingly, home and foreign oil efficiencies (Z_1^o and Z_2^o) are, indeed, two of the fifteen exogenous shock processes of the model borrowed from Bodenstein and Guerrieri (2011) :

$$ln(Z^o_{1,t}) = (1+\rho_1^{zo} - \rho_{12}^{zo})ln(Z^o_{1,t-1}) - \rho_1^{zo} ln(Z^o_{1,t-2}) + \sigma_1^{zo}\varepsilon_{1,t}^{zo} \tag{3.1}$$

$$ln(Z^o_{2,t}) = (1+\rho_2^{zo} - \rho_{12}^{zo})ln(Z^o_{2,t-1}) - \rho_1^{zo} ln(Z^o_{2,t-2}) + \sigma_2^{zo}\varepsilon_{2,t}^{zo} \tag{3.2}$$

In the expression 3.1 (3.2) the term $Z^o_{1,t}$ ($Z^o_{2,t}$) represents the home (foreign) stochastic process that influences the oil efficiency in production. Besides the same shock $Z^o_{1,t}$ ($Z^o_{2,t}$) that affects home (foreign) oil efficiency in production also affects the home (foreign) oil efficiency of consumption. ρ_1^{zo} (ρ_2^{zo}) is a home (foreign) oil efficiency growth AR(1) coefficient. ρ_{12}^{zo} is a coefficient that measures the correlation in the level of oil efficiency between home and foreign countries and σ_1^{zo} (σ_2^{zo}) measures the oil efficiency standard deviation of innovation.

Beyond the measure of the oil efficiency aggregate foreign bloc, the authors also measured oil efficiency of individual foreign countries based on the growth-accounting studies of Solow (1957) (see eq. 2 from Solow (1957)) and Griliches and Jorgenson (1966)). By using the first order conditions for oil use by foreign firms $O^y_{2,t}$ and households $O^c_{2,t}$ they rewrite foreign oil efficiency growth as:

$$\begin{aligned}
ln(\frac{Z^o_{2,t}}{Z^o_{2,t-1}}) + (\mu_1^{zo} - 1) &= \rho_2^o ln(\frac{O_{2,t}}{O_{2,t-1}}) + (1+\rho_2^o) ln(\frac{P^o_{2,t}}{P^o_{2,t-1}}) \\
+ln(\frac{GDP_{2,t}}{GDP_{2,t-1}}) - (1+\rho_2^o) ln(&\frac{e_{1,t}P^{gdp}_{2,t}GDP_{2,t}}{e_{1,t-1}P^{gdp}_{2,t-1}GDP_{2,t-1}}) + ln(\frac{S_{2,t}}{S_{2,t-1}})
\end{aligned} \tag{3.3}$$

In the expression 3.3 the term μ_1^{zo} denotes a foreign constant rate of oil efficiency gains at the balanced growth path. Growth in efficiency relative to the balanced growth path is measured by the term $ln(\frac{Z^o_{2,t}}{Z^o_{2,t-1}})$. $ln(\frac{S_{2,t}}{S_{2,t-1}})$ is a correction term for changes in the composition of aggregate oil demand (see Bodenstein and Guerrieri (2012) for a detailed explanation) and ρ_2^o the oil price elasticity of demand of the foreign bloc. Moreover, the balanced growth path of the model imposes that the oil efficiency must grow over time to bridge the gap between the growth rates of labor augmenting technology and oil supply $\mu_{zo} = \frac{\mu_z}{\mu_o}$. Consequently, the price of oil is expected to grow at the rate μ_{zo} unconditionally Stefanski (2011).

Over the period 1984 to 2008 country-by-country measures of oil efficiency consistent with the foreign aggregate efficiencies and μ_1^{zo}, ρ_2^{zo} estimated parameters were constructed by the authors. Accordingly to their calculates oil efficiency have improved at the quarterly rate of 0.32 percent along the balanced growth path given the relationship $\mu_{zo} = \frac{\mu_z}{\mu_o}$. Consequently, the trend growth in the real price of oil would be also 0.32 percent per quarter, or roughly 1.3 percent per year. With the specific research Bodenstein and Guerrieri (2011) outlined that changes in oil efficiency have a direct influence in oil demand. It seems that movements in oil efficiency were able to capture changes in consumption patterns or production processes. Accordingly to their estimates of most developed countries, China and Mexico oil efficiency showed significant faster growth than μ_{zo} in the 1980s and 1990s. After the late 1990s, however, foreign efficiency improvements slowed down causing a narrow gap between actual oil efficiency and cumulative trend growth in oil efficiency in a inverted U-shaped pattern. Accordingly to Bodenstein and Guerrieri (2011) this inverted U-shaped pattern of the evolution of foreign oil efficiency is shared by many countries, including Japan (see fig. I.10) but being less evident in the U.S. (see I.11), and is not merely a consequence of aggregation. Furthermore, the authors found that movements in foreign oil efficiency were of principal importance in the determination of oil demand and prices over the period 1984 to 2008 both at business-cycle and longer frequencies.

3.3 Bayesian estimation

Contrary to Bodenstein et al. (2012) who applied the maximum likelihood method we adopt instead a bayesian estimation approach. Furthermore, opposing Bodenstein and Guerrieri (2012), the estimates of scale of the shock process and autoregressive parameters for home and foreign shocks are not to be the same in the case of the shocks to productivity, oil intensity, consumption preferences, and import preferences. All estimates are based on 15 quarterly observed times series from the United States (or Japan) and foreign block economy:

the home GDP, the home oil production, the home price of oil (deflated by the respective GDP deflator), the home hours worked per capita, the home real trade-weighted exchange rate, the home GDP share of private consumption expenditures, the home GDP share of oil imports, the home GDP share of non-oil goods imports, the home GDP share of goods exports, the home GDP share of fixed investment, the home GDP share of government expenditures, the home level of core PCE inflation, the home wage inflation and home interest rates. Relative to foreign variables the variable weight method of growth (BDH method) (Beyer and Juselius, 2010) was the aggregation method applied. The trade weights (narrow or broad) were from http://www.bis.org/statistics/eer/. Growth of Euro area (12 countries), previous 1999, was calculated accordingly to Buldorini et al. (2002) and our sample period is from 1973:QIV through 2013:QIV. As we were dealing with a nonlinear model for Log-Linearization the data were related to model-implied variables by the measurement equations expressed in Appendix B. The sources of the observed series are practically the same for the U.S. as for the Japanese economy (see Appendix A).

3.3.1 Priors distributions

Generally speaking four types of parameters appear in usual DSGE models conditions: technological parameters such the depreciation rate of capital commonly denoted by δ; preferences parameters such as the discount factor commonly denoted by β; steady state parameters such the steady state nominal interest rate; and parameters of driving process such K-L substitution elasticities. Contrary to what one might think priors distributions have a considerable impact on posterior estimates and model comparison. In order to minimize such impacts a framework for constructing priors for different classes of parameters was provided by Negro and Schorfheide (2008). Despite its advantages the method have not been really applied in the most recent literature. Due to some time restrictions our priors distributions for the U.S and the Japanese economy were also mostly based in the published literature.

Japan Priors distributions

Few papers have been published regarding DSGE models that were calibrated for the Japanese economy. Hirose (2014b), Fueki et al. (2010), Iiboshi et al. (2015), Hirose (2014a), and Ichiue et al. (2011) are the most remarkable literature on the subject. Our priors of Monetary Policy parameters ($\gamma_1^i, \gamma_1^\pi, \gamma_1^y, \tau_1^w, \tau_1^p$) are the same as the ones used by Fueki et al. (2010), however, the prior distributions of Hirose (2014b) are quite similar. Is noteworthy to refer the considerable higher values of Monetary Policy parameters, namely, γ_1^π, γ_1^y when compared to Bodenstein et al. (2012) estimates for the U.S. Proceeding, steady state parameters' priors distributions which are related to the balanced growth rate of hours worked, inflation rate and real interest rate are set to be the normal distribution with a mean based on the sample average of the corresponding observable data. Weights in production and consumption functions $(\omega_k, \omega_{oy}, \omega_{oc}, \omega_{mc}, \omega_{mi})$ are fixed. They were calibrated to the sample average mean of our observable data. Priors for the shock persistence parameters, $(\rho_x, x \in \rho_1^{\theta w}, \rho_1^{\theta p}, \rho_1^{zi}, \rho_1^{zc}, \rho_1^{zg}, \rho_1^{yo}, \rho_1^{zo}, \rho_1^{zm}, \rho_2^{\theta w}, \rho_2^{\theta p}, \rho_2^{zi}, \rho_2^{zc}, \rho_2^{zg}, \rho_2^{yo}, \rho_2^{zo}, \rho_2^{zm})$ are set to be the Normal distribution with a mean corresponding to the estimated values of Bodenstein et al. (2012) but only in the case of the world technology (ρ_2^z), world oil efficiency (ρ_2^{zo}), oil supply (y_1^o), oil efficiency (ρ_1^{zo}) as, unfortunately, we didn't find estimates applied to the Japanese economy in the literature. For a more detailed description see Table 1. Shocks Processes and Table 3. Estimation Results from Bodenstein et al. (2012). All the remaining shock persistence prior distributions are set to the respective posteriors distributions found by Hirose (2014b), including other non persistence parameters as $\hat{\theta}_1^p$, $\hat{\theta}_1^w$, $\bar{\pi}_1^{core}$. Of particular interest are persistence parameters related to imports and technology as their values are significant higher than the correspondent U.S. estimates and wage and price markup which are considerably lower.

Additional parameters such as habits in consumption (κ_1), investment adjustment cost (ψ_1^i), labor supply elasticity (χ_1), calvo price and wage parameters (ξ_1^w, ξ_1^p), lagged price and wage indexation (ι_1^w, ι_1^p), are equally set to the posteriors distributions found by Hirose (2014b) and the elasticity of substitution between domestic goods and imports (ρ_1^{zc}) is based in Chen et al. (2012). The values of χ_1, ψ_1^i, ξ_1^w are remarkably lower than the ones estimated by Bodenstein et al. (2012) for the U.S. Japanese calvo wage parameter (ξ_1^w) is, inclusively, lower than the Japanese calvo price. On the contrary the values of ρ_1^{zc}, ι_1^w, ι_1^p are considerably higher than the estimated for the U.S.

As usually in the literature we also opted by the inverse gamma-1(-2) as the prior distribution for the standard deviations (resp. variance) of the shock innovations $(\sigma_x, x \in \sigma_1^{\theta w}, \sigma_1^{\theta p}, \sigma_1^{zi}, \sigma_1^{zc}, \sigma_1^{zg}, \sigma_1^{yo}, \sigma_1^{zo}, \sigma_1^{zm}, \sigma_2^{\theta w}, \sigma_2^{\theta p}, \sigma_2^{zi}, \sigma_2^{zc}, \sigma_2^{zg}, \sigma_2^{yo}, \sigma_2^{zo}, \sigma_2^{zm})$ [2]. Moreover, for the mean of the standard deviations (resp. variance) of each shock innovation we chose, as previously, the estimated value of the U.S. economy published by Bodenstein et al. (2012) for the world technology (σ_2^z), world oil efficiency (σ_2^{zo}), oil supply (y_1^o), oil efficiency (σ_1^{zo}) and posteriors distributions found by Hirose (2014b) for the remaining shock persistence parameters. Altogether import and government' standard deviations are higher than the U.S. estimates while the wage markup standard deviation is significatly lower. Further details about our Prior distributions (see Posteriors distributions in table G.1) estimates are provided in table C.5 in Appendix C .

[2] Accordingly to Adjemian (2010) this is because in linear models with gaussian perturbation, the Normal (for the parameters) – Inverse Gamma (for the variance of the error) prior is conjugate. Obviously this is not true for DSGE models, subsequently there is no computational advantage in choosing the inverse gamma prior.

U.S. Priors distributions

The U.S. prior means were essentially based in Bodenstein et al. (2012) estimated parameters while standard errors prior deviations are more or less similar to Japan. As described above steady state parameters' priors distributions of hours worked, inflation rate and real interest rate are also set to be the normal distribution with a mean based on the sample average of the corresponding observable data. Likewise weights in production and consumption functions ($\omega_k, \omega_{oy}, \omega_{oc}, \omega_{mc}, \omega_{mi}$) are fixed and calibrated to the average mean of our observable data. Priors of the shock persistence parameters ($\rho_x, x \in \rho_1^{\theta w}, \rho_1^{\theta p}, \rho_1^{zi}, \rho_1^{zc}, \rho_1^{zg}, \rho_1^{yo}, \rho_1^{zo}, \rho_1^{zm}, \rho_2^{\theta w}, \rho_2^{\theta p}, \rho_2^{zi}, \rho_2^{zc}, \rho_2^{zg}, \rho_2^{yo}, \rho_2^{zo}, \rho_2^{zm}$) are also set to be the Normal distribution with a mean corresponding to the estimated values stated in Table 3. Estimation Results of Bodenstein et al. (2012). Once more we opted by the inverse gamma-1(-2) as a prior for the standard deviations (resp. variance) of the shock innovations ($\sigma_x, x \in \sigma_1^{\theta w}, \sigma_1^{\theta p}, \sigma_1^{zi}, \sigma_1^{zc}, \sigma_1^{zg}, \sigma_1^{yo}, \sigma_1^{zo}, \sigma_1^{zm}, \sigma_2^{\theta w}, \sigma_2^{\theta p}, \sigma_2^{zi}, \sigma_2^{zc}, \sigma_2^{zg}, \sigma_2^{yo}, \sigma_2^{zo}, \sigma_2^{zm}$) [3] . The mean of the standard deviation (resp. variance) of each shock innovation is also the estimated value for the U.S. economy stated in Table C.5 in Appendix C. Estimation Results of Bodenstein et al. (2012).

Foreign block Priors distributions

The priors for the foreign block are very similar to the U.S. priors (see table C.6 in Appendix C). Although some priors had been specifically estimated by Bodenstein et al. (2012) for the foreign block, namely: the Foreign Technology, standard deviation of innovation (σ_2^z), the Foreign Oil Supply, growth AR coefficient (ρ_{22}^{yo}), the Foreign Oil Supply, level error of correlation coefficient (ρ_{21}^{yo}), the Foreign Oil Supply, standard deviation of innovation (ρ_2^{yo}), the Foreign Oil Efficiency, standard deviation of innovation (ρ_2^{zo}), the Foreign Consumption, standard deviation of innovation (ρ_2^{zc}) and the Foreign Imports, standard deviation of innovation (ρ_2^{zm}).

[3] Accordingly to Adjemian (2010) this is because in linear models with gaussian perturbation, the Normal (for the parameters) – Inverse Gamma (for the variance of the error) prior is conjugate. Obviously this is not true for DSGE models, there is no computational advantage in choosing the inverse gamma prior.

Chapter 4

Results

The main model's results are stated in the present chapter. The first three sections are addressed to a briefly analysis of output results that were expressly conceived by Dynare developers in order to check and validate or refute the model's macroeconomic results. In section 4.1 we identify the parameters with a high impact on the model's results through an identification and sensitivity analysis. Section 4.2 states a brief summary of our check mode plots and posterior distributions. The Monte Carlo Markov Chain (MCMC) univariate diagnostics based on Brooks and Gelman (1998) and the multivariate convergence diagnostic are present in section 4.3. We proceed with a shock decomposition analysis. The impact of oil exergy efficiency on relevant macroeconomic variables is discussed in subsection 4.4.1 while the contribution of home and world oil efficiency shocks in the U.S. and Japan oil consumption and oil prices is addressed in subsection 4.4.2. Subsection 4.4.2 also depicts a comparison of our home and world oil efficiency shocks with the observed crude oil and aggregate exergy efficiencies computed by Warr et al. (2010).

4.1 Identification analysis

As already noted new-Keynesian DSGE models are characterized by a complex combination of parameter values. Therefore the knowledge of how results can be obliterated by these values is an information of the utmost importance. Dynare provides an interface to the global sensitivity analysis (GSA) toolbox (developed by the Joint Research Center (JRC) of the European Commission), which is now part of the official Dynare distribution. The GSA toolbox can be used to answer several questions, namely, to measure the impact of estimated values of the unknown parameters on the model's results. This is often described as an identification and sensitivity analysis. The identification strength of the parameters are based on the Fischer information matrix that is either computed analytically (Iskrev, 2011) or based on simulations. For bayesian estimation the identification and sensitivity strength of the parameters are normalized by either the parameter at the prior mean (depict in the blue bars of the bar charts F.1 and F.2) or by the standard deviation at the prior mean (depict in the yellow bars of the bar charts F.1 and F.2) (see Ratto and Iskrev (2011), p. 15).

Intuitively, the bars of the figures F.1 and F.2 represent the normalized curvature of the log likelihood function at the prior mean in the direction of the parameter. If the parameter's strength is 0, what doesn't succeed for any parameter of the upper diagram of fig.F.1, the parameter is not identified as the likelihood function is flat in this direction. In contrast, the larger the absolute value of the bars, the stronger is the identification. In the upper panel (identification strength with moments information matrix) of the corresponding figure a strong identification is observed, indeed, with respect to the prior mean of ι_1^w, ρ_1^{zo}, ρ_1^{zow}, ρ_1^{zg}, π_1^*, μ_1^o, μ_1^z, μ_2^o, μ_2^z parameters. Furthermore, a stronger identification of the standard deviation at the prior mean of the previous parameters and σ_2^{zc} is observed. On their side the ρ_2^{yo} and ρ_2^{zc} parameters show a weak identification regarding their prior mean but a strong identification with respect to the parameter's prior mean standard deviation.

The identification effects shown in the upper panel of fig.F.1 are decomposed in the lower panel of the corresponding figure. Accordingly to Pfeifer (2014) a weak identification can be due to either other parameters linearly compensating/replacing the effect of a parameter (i.e. parameters having exactly the same effect on the likelihood, see collinearity partterns in fig. F.4 in Apppendix F) or the fact that the likelihood does not change at all with the respective parameter. This latter effect is called sensitivity and is computed according to the formula (12) in Ratto and Iskrev (2011)). As previously, sensitivity weighting can take place either with the prior mean (blue bars of the bar charts F.1 and F.2) or the prior standard deviation (yellow bars of the bar charts F.1 and F.2). As expected the bottom panel does not depicts a zero sensitivity for any of the model's parameters but confirms a very weak sensitivity regarding to the prior mean of ι_2^w, ρ_2^{zo}, ρ_2^{yo} what confirms that the likelihood barely changes with respect to the corresponding prior mean parameters. The smallest singular values from the singular value decomposition of the Fischer information matrix, depicted in fig. F.7, also corroborates the very weak sensibility of the mentioned parameters. On the contrary, we observe a strong sensitivity of the model to the prior mean of μ_1^o, μ_1^z, μ_2^o, μ_2^z, ρ_1^{zg}, ρ_2^{zg}, ι_1^w, ρ_{11}^{zo}, ρ_{11}^{zow}, ρ_2^y parameters. Besides a stronger identification of the standard deviation at the prior mean of μ_1^o, μ_1^z, μ_2^o, μ_2^z, ρ_1^{zg}, ρ_2^{zg}, ρ_{11}^{zo}, ρ_{11}^{zow}, ρ_2^y, is also confirmed by the bottom panel of F.1 as by the largest singular values depicted in fig. F.8.

The identification and sensitivity strength of the parameters of the U.S. is plot in fig. F.2. A weaker identification for the prior mean of the following parameters ρ_{12}^{zo}, γ_2^{dpc}, ι_2^p, $\rho_2^{\theta_p}$, $\rho_2^{\theta_w}$ is observed. Notwithstanding, the sensitivity of the prior mean of the mentioned parameters is not so weak. Therefore, we infer that the small strength identification of these parameters is rather due to other parameters linearly compensating/replacing their effect as confirmed by fig. F.5 in Appendix F. A strong identification with respect to the prior mean of μ_1^o, μ_1^z, μ_2^o, μ_2^z, ρ_1^{zg}, ξ_1^w, ρ_{11}^{zow}, ρ_{12}^{zow} parameters is depicted, instead, in the upper panel of the respective figure. Besides a stronger identification of the standard deviation at the prior mean of μ_1^o, μ_1^z, μ_2^o, μ_2^z, ρ_1^{zg}, ξ_1^w, ρ_{11}^{zow}, ρ_{12}^{zow} and ρ_1^v, σ_1^{zi} χ_2 is also behold. Overall the sensitivity strength of these parameters is confirmed in the bottom panel of the same figure as by the largest singular values depicted in fig. F.6. From the mentioned above is noteworthy the strong sensitivity of the model's results to balanced growth path parameters μ_1^o, μ_1^z, μ_2^o, μ_2^z.

4.2 Mode Check Plots

Parameter values for which the model could not be solved due to e.g. violations of the Blanchard-Kahn conditions (indeterminacy or no bounded solution) are also indicated as big red dots in mode check plots. From our figures there are few parameters where violations of the Blanchard-Kahn conditions are observed for a given range of values, namely, μ_1^z, μ_1^o, ρ_1^{zg}, ρ_1^{zi}, $\rho_1^{\theta_w}$, ξ_1^p. σ_1^{yo} for the U.S.. μ_2^z, μ_2^o, ρ_2^{zg}, ρ_2^{zi}, $\rho_2^{\theta_w}$, ρ_2^{zc}, $\sigma_2^{\theta_w}$ for the foreign bloc and μ_1^z, μ_1^o, ρ_1^{zg}, ρ_1^{zi}, $\rho_1^{\theta_w}$, ξ_1^p for Japan. See the check mode plots D.2, D.4 in appendix for Japan and the U.S. models respectively. Posterior distributions of Japan, U.S. and foreign bloc economies, that are pretty in line with the priors values, are described in the tables below.

Table 4.1 Posteriors distributions from the Bayesian estimation of the parameters of the Japanese economy

Parameters	Simb	Mean	90% HPD interval	postdev
JP Trend Depreciation Rate of Capital	μ_3^z	.0251	.0250 .0251	.0001
JP Trend Growth in Oil Supply	μ_3^o	1.0026	1.0026 1.0026	.015
JP Trend Growth in Technology Growth	μ_3^z	1.0083	1.0081 1.0084	.15
JP Labor Supply Elasticity	χ_3	3.5	3.5 3.5	.00001
JP Habits in Consumption	κ_3	.605	.605 .605	.0001
JP Investment Adjustment Cost	ψ_3^i	1.24	1.24 1.24	.0001
JP Trade Subs. Elasticity	ρ_3^c	−10	−10 −10	.0001
JP Oil Subs. Elasticity	ρ_3^o	−1.73	−1.73 −1.73	.0001
JP Capital Subs. Elasticity	ρ_3^k	−2.	−2. −2.	.0001
JP Calvo Price Parameter	ξ_3^p	.8	.8 .8	.00001

Continued on next page

Table 4.1 – continued from previous page

Parameters	Simb	Mean	90% HPD interval	postdev
JP Calvo Wage Parameter	ξ_3^w	.7	.7 .7	.00001
JP Policy Rate Smoothing	γ_3^i	.9	.9 .9	.00001
JP Weight on Inflation in M. P. R.	$\gamma\pi_3$	1.2	1.2 1.2	.0001
JP Weight on Output Gap in M. P. R	γ_3^y	.2	.2 .2	.0001
JP Lagged Wage Indexation	ι_3^p	.8	.8 .8	.00001
JP Lagged Price Indexation	ι_3^w	.7	.7 .7	.00001
JP Mon. Policy, AR(1) coef.	ρ_3^π	.4	.4 .4	.00001
JP Mon. Policy, st. dev. of Innov.	σ_3^π	.057	.057 .057	.00001
JP Investment Technology, AR(1) coef.	ρ_3^{zi}	.97	.97 .97	.0001
JP Investment Technology, st. dev.	σ_3^{zi}	.023	.023 .023	.00001
JP Gov. Expenditure, AR(1) coef.	ρ_3^{zg}	.93	.93 .93	.00001
JP Gov. Exp., st. dev. of innov.	σ_3^{zg}	1.52	1.52 1.52	.00001
JP Technology, growth AR(1) coef.	ρ_{33}^z	.359	.359 .359	.0001
JP Technology, level error corr. coef.	ρ_{23}^{zc2}	.0001	.0001 .0001	.00001
JP Technology, st. dev. of innov.	σ_3^z	1.662	1.662 1.662	.00001
JP Price Markup, AR(1) coef.	$\rho_3^{\theta p}$	.294	.294 .294	.00001
JP Price Markup, st. dev. of innov.	$\sigma_3^{\theta p}$	.434	.434 .434	.00001
JP Wage Markup, AR(1) coef.	$\rho_3^{\theta w}$	.289	.289 .289	.0001
JP Wage Markup, st. dev. of innov.	$\sigma_3^{\theta w}$	.457	.457 .457	.0005
JP Oil Supply, growth AR(1) coef.	ρ_{33}^{yo}	.124	.124 .124	.00001
JP Oil Supply, level error corr. coef.	ρ_{23}^{yo}	.0001	.0001 .0001	.0001
JP Oil Supply, st. dev. of innov.	σ_3^{yo}	.025	.025 .025	.00001
JP Oil Efficiency, growth AR(1) coef.	ρ_{33}^{zo}	.0001	.0001 .0001	.0001
JP Oil Efficiency, level error corr. coef.	ρ_{23}^{zo}	.014	.0144 .0144	.0001
JP Oil Efficiency, st. dev. of innov.	σ_3^{zo}	.046	.0462 .0462	.0002
JP Consumption, AR(1) coef.	ρ_3^{zc}	.96	.96 .96	.00001
JP Consumption, st. dev. of innov.	σ_3^{zc}	4.67	4.67 4.67	.0001
JP Import, growth AR(1) coef.	ρ_{33}^{zm}	.856	.856 .856	.00001
JP Import, level error corr. coef.	ρ_{23}^{zm}	.002	.0019 .002	.00001
JP Import, st. dev. of innov.	σ_3^{zm}	3.509	3.509 3.509	.00001

Table 4.2 Posteriors distributions from the Bayesian estimation of the parameters of the U.S. economy

Parameters	Simb	Mean	90% HPD interval	postdev
U.S.Trend Depreciation Rate of Capital	μ_3^z	.034	.0336 .0337	.00001
U.S. Steady State Growth Oil Supply	μ_1^o	1.003	1.0021 1.0024	.15
U.S. Steady State Technology Growth	μ_1^{zo}	1.006	1.0061 1.0064	.15
U.S. Labor Supply Elasticity	χ_1	59.54l	59.54 59.54	.00001
U.S. Habits in Consumption	κ_1	.651	.6511 .6512	.0001
U.S. Investment Adjustment Cost	ψ_1^i	3.515	3.5153 3.5155	.0001
U.S. Trade Subs. Elasticity	ρ_1^c	1.321	1.3208 1.3209	.0001
U.S. Oil Subs. Elasticity	ρ_1^o	-1.732	-1.7314 -1.7316	.0005
U.S. Capital Subs. Elasticity	ρ_1^k	-1.23	-1.23 -1.23	.0001
U.S. Calvo Price Parameter	ξ_1^p	.814	.8138 .8140	.0001
U.S. Calvo Wage Parameter	ξ_1^w	.890	.89 .8901	.0001
U.S. Policy Rate Smoothing	γ_1^i	.655	.6553 .6554	.00001
U.S. Weight on Inflation in M. P. R.	γ_π	.191	.1907 .1909	.0001
U.S. Weight on Output Gap in M. P. R	γ_1^γ	$-.00001$	$-.0001$ $-.00001$	00001
U.S. Lagged Wage Indexation	ι_1^p	.0001	$-.0001$ $-.00001$	.00001
U.S. Lagged Price Indexation	ι_1^w	.0001	$-.0001$ 0.0001	.00001
U.S. Mon. Policy, AR(1) coef.	ρ_1^π	.403	.4026 .4026	.0000
U.S. Mon. Policy, st. dev. of Innov.	σ_1^π	.022	.0216 .0219	.0002
U.S. Investment Technology, AR(1) coef.	ρ_1^{zi}	.906	.9058 .9060	.0001
U.S. Investment Technology, st. dev.	σ_1^{zi}	.027	.0268 .0271	.0002
U.S. Gov. Expenditure, AR(1) coef.	ρ_1^{zg}	.999	.999 .9991	.00001
U.S. Gov. Exp., st. dev. of innov.	σ_1^{zg}	.025	.0247 .0249	.0002
U.S. Technology, growth AR(1) coef.	ρ_{11}^z	.216	.2163 .2164	.0001
U.S. Technology, level error corr. coef.	ρ_{21}^{z2}	.0001	.0000 .0002	.0001
U.S. Technology, st. dev. of innov.	σ_1^z	.007	.0072 .0072	0.0001
U.S. Price Markup, AR(1) coef.	$\rho_1^{\theta p}$	.740	.7401 .7401	.0000
U.S. Price Markup, st. dev. of innov.	$\sigma_1^{\theta p}$	.477	.4773 .4774	.0001
U.S. Wage Markup, AR(1) coef.	$\rho_1^{\theta w}$	.987	.9868 .9870	.0001
U.S. Wage Markup, st. dev. of innov.	$\sigma_1^{\theta w}$	3.699	3.6987 3.6989	.00001
U.S. Oil Supply, growth AR(1) coef.	ρ_{11}^{yo}	.124	.1243 .1244	.0001
U.S. Oil Supply, level error corr. coef.	ρ_{21}^{yo}	.000	.000 .0002	.0001

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Table 4.2 – continued from previous page

Parameters	Simb	Mean	90% HPD interval	postdev
U.S. Oil Supply, st. dev. of innov.	σ_1^{yo}	.025	.0254 .0255	.0001
U.S. Oil Efficiency, growth AR(1) coef.	ρ_{11}^{zo}	.000	.0001 .0002	.0001
U.S. Oil Efficiency, level error corr. coef.	ρ_{21}^{zo}	.014	.0143 .0144	.00001
U.S. Oil Efficiency, st. dev. of innov.	σ_1^{zo}	.048	.0477 .0482	.0005
U.S. Consumption, AR(1) coef.	ρ_1^{zc}	.919	.9188 .9189	.0001
U.S. Consumption, st. dev. of innov.	σ_1^{zc}	.648	.6484 .6486	.0001
U.S. Import, growth AR(1) coef.	ρ_{11}^{zm}	.0001	−0.00001 0.0002	0.0001
U.S. Import, level error corr. coef.	ρ_{21}^{zm}	.002	.0019 .0019	.00001
U.S. Import, st. dev. of innov.	σ_1^{zm}	.027	.0268 .0269	.0001

Table 4.3 Posteriors distributions from the Bayesian estimation of the parameters of the foreign economy

Parameters	Simb	Mean	90% HPD interval	postdev
U.S.Trend Depreciation Rate of Capital	μ_3^z	.025	.0250 0.0251	.0002
For. Trend in Growth Oil Supply	μ_2^o	1.003	1.0025 1.0027	.15
For. Trend in Technology Growth	μ_2^z	1.006	1.0056 1.0058	.15
For. Labor Supply Elasticity	χ_2	59.540	59.5401 59.5402	.0001
For. Habits in Consumption	κ_2	.651	.6511 .6513	.0001
For. Investment Adjustment Cost	ψ_2^i	3.5169	3.5169 3.5169	1
For. Trade Subs. Elasticity	ρ_2^c	1.321	1.3209 1.3210	.0001
For. Oil Subs. Elasticity	ρ_2^o	−2.598	−2.5976 −2.5978	.0001
For. Capital Subs. Elasticity	ρ_2^k	−2.220	−2.2200 −2.2199	.0001
For. Calvo Price Parameter	ξ_2^p	.813	.8138 .8141	.0001
For. Calvo Wage Parameter	ξ_2^w	.890	.8900 .8899	.00001
For. Policy Rate Smoothing	γ_2^i	.655	.6553 .6554	.0001
For. Weight on Inflation in M. P. R.	$\gamma\pi_2$	.191	.1906 .1908	.0001
For. Weight on Output Gap in M. P. R	γ_2^y	.000	.0001 .0002	.0001
For. Lagged Wage Indexation	ι_2^p	.500	.4999 .4999	.0000
For. Lagged Price Indexation	ι_2^w	.500	.4999 .5000	.00001
For. Mon. Policy, AR(1) coef.	ρ_2^π	.500	.4999 .5000	.00001

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Table 4.3 – continued from previous page

Parameters	Simb	Mean	90% HPD interval		postdev
For. Mon. Policy, st. dev. of Innov.	σ_2^{π}	.022	.0216	.0217	.0002
For. Investment Technology, AR(1) coef.	ρ_2^{zi}	.906	.9060	.9061	.0001
For. Investment Technology, st. dev.	σ_2^{zi}	.027	.0267	.0270	.00001
For. Gov. Expenditure, AR(1) coef.	ρ_2^{zg}	.999	.9990	.9990	.00001
For. Gov. Exp., st. dev. of innov.	σ_2^{zg}	.025	.0247	.0249	.0002
For. Technology, growth AR(1) coef.	ρ_{22}^{z}	.216	.2161	.2162	.00001
For. Technology, level error corr. coef.	ρ_{21}^{zc2}	.000	.0000	.0002	.0001
For. Technology, st. dev. of innov.	σ_2^{z}	.0110	.0110	.0110	.00001
For. Price Markup, AR(1) coef.	$\rho_2^{\theta p}$	.740	.7401	.7402	.0001
For. Price Markup, st. dev. of innov.	$\sigma_2^{\theta p}$	.477	.4773	.4774	.0001
For. Wage Markup, AR(1) coef.	$\rho_2^{\theta w}$	.977	.9768	.9769	.00001
For. Wage Markup, st. dev. of innov.	$\sigma_2^{\theta w}$	3.699	3.6987	3.6988	.00001
For. Oil Supply, growth AR(1) coef.	ρ_{22}^{yo}	.0001	.0001	.0002	.0001
For. Oil Supply, level error corr. coef.	ρ_{21}^{yo}	.038	.0378	.0379	.00001
For. Oil Supply, st. dev. of innov.	σ_2^{yo}	.018	.0179	.0181	.0001
For. Oil Efficiency, growth AR(1) coef.	ρ_{22}^{zo}	.0001	.0000	.0002	.0001
For. Oil Efficiency, level error corr. coef.	ρ_{21}^{zo}	.014	.0144	.0144	.00001
For. Oil Efficiency, st. dev. of innov.	σ_2^{zo}	.127	.1269	.1270	.0000
For. Consumption, AR(1) coef.	ρ_2^{zc}	.919	.9188	.9189	.00001
For. Consumption, st. dev. of innov.	σ_2^{zc}	.717	.7174	.7175	.0005
For. Import, growth AR(1) coef.	ρ_{22}^{zm}	.0001	.0001	.0002	.0001
For. Import, level error corr. coef.	ρ_{21}^{zm}	.041	.0413	.0414	.00001
World Technology, growth AR(1) coef.	ρ_{22}^{zw}	.010	.0100	.0101	.0001
World Technology, level error corr. coef.	ρ_{21}^{zw}	.001	.0010	.0011	.0003
World Technology, st. dev. of innov.	σ_2^{zw}	.001	.001	.0012	.0001
World Oil Efficiency, growth AR(1) coef.	ρ_{22}^{zow}	.001	.0010	.0011	.0001
World Oil Efficiency, level error corr. coef.	ρ_{21}^{zow}	.001	.0009	.0010	00001
World Oil Efficiency, st. dev. of innov.	σ_2^{zow}	.001	.0009	.0010	.00001

4.3 Convergence Diagnostics

Our posterior distributions were simulated with the Metropolis-Hastings algorithm. A useful introduction to the topic is exposed in Chib and Greenberg (1995). The Monte Carlo Markov Chain (MCMC) univariate diagnostics based on Brooks and Gelman (1998) and the Multivariate convergence diagnostic (which does not follow Brooks and Gelman (1998) strictly) were automatically generated by Dynare's estimation command as we run 1000000 draws (see Appendix E for further information). A superposition and horizontal stabilisation of both lines (chains), in the Multivariate convergence diagnostic, is reached after 150000 draws in the case of the U.S. model and Japan. The observation confers some support to the conviction that convergence has been reached.

4.4 Shock Decomposition Analysis

Nowadays shock decomposition is a standard procedure to easily map the contributions of estimated structural shocks to observed data series. An example of an important variable is the output gap, where one can clearly trace contributions of input data (Andrle, 2013b) using the methods described in Andrle (2013a). These methods are often based on the application of filters such as the Kalman filter (smoother) algorith (see Durbin and Koopman (2001) among others). They have been, recently, implemented in Dynare through the `shock_decomposition` command in order to allow us to compute and display shock decomposition according to our model for a given sample.

Our shock decomposition is computed for the `posterior_mode`. As our model has 22 exogenous shocks (see section 3.2) we included them into 7 groups (detailed information is exposed in Appendix G). We, firstly, focused the analysis on the impact of several shocks, by attributing a special attention to home and world technology shocks, on few endogenous variables, namely, on GDP growth, interest rates, wages and core inflation. Secondly, we addressed our attention to the impact of home and foreign oil efficiency shocks on U.S. and Japanese's oil consumption and oil prices. In the first and in the second case the shock decomposition analysis is here firstly discussed for the U.S. and subsequently for the Japanese economy.

4.4.1 Economic reaction to the post-World War II oil shocks

As already described in the section 2.2.1 the predominantly economic reaction to the post-world war II oil supply disruptions is characterized by higher inflation due to net oil prices increases, proceed by higher short-term interest rates, reduced terms of trade of manufacturing industry, low level of employment and utilization capacity which induces a fall in the real wage, a temporary reduction in real GDP growth and a depreciating currency with respect to the dollar (Flemming, 1987; Kilian, 2008a). In this section we propose to explore, through a shock decomposition analysis, the potential importance of two main channels of the transmission of exogenous shocks, real wages rigidities and monetary tightening, appointed by Kilian (2008b), in the economies of U.S. and Japan.

United States

The shock decomposition pattern of the U.S. core inflation (Appendix I, fig.I.1) is very similar to the U.S. wage inflation (Appendix I, fig.I.3) as, without taking into account punctual divergences coincident with oil supply disruptions, the tendency of both observable variables is very alike (Appendix A, fig.A.1 and fig.A.4). The results show a lack of exogenous oil supply shocks in the core inflation decomposition plot (Appendix I, fig.I.1), specifically in the 70s, where supply and home technology shocks were observed instead. Subsequently, if there were any relation of cause between higher levels of core inflation and oil supply disruptions it wasn't a direct one but through the supply chain. Moreover, the results could also support Kilian (2008a)'s speculation of a predominant contribution from other endogenous factors rather than oil supply shocks to the 70s high inflation (see section 2.2.2). Besides, U.S. interest rates experienced almost negative monetary shocks before 2000s and positive monetary shocks afterwards (Appendix I, fig.I.2). Levels of reduction intensity of negative monetary shocks on interest rates were, although, noticed after oil supply disruptions what reasonably supports Bernanke et al. (1997)'s idea that U.S. high temporary interest rates after post-WWII oil supply disruptions had been supported by monetary policies. The subsequent impact on U.S. wage inflation (see section 2.2.1) is depicted in fig.I.3, Appendix I, through negative supply shocks that occurred after the post-WWII oil supply disruptions.

U.S. oil supply shocks (Hamilton, 2011; Kilian, 2008b) are clear depicted in the U.S. GDP growth shock decomposition[1]. Significant contributions from other positive shocks such as home technology and oil efficiency, from the 70s until the 2000s, are also depicted in fig.I.4, Appendix I. On the contrary, over the last decade, as in the case of wage and core inflation's shock decompositions, a negative contribution of home oil efficiency shocks to GDP growth counterbalanced by positive shocks of U.S. oil supply is observed instead. Post-world war II oil supply disruptions (Hamilton, 2011; Kilian, 2008b) are also more

[1] Perhaps due to the energy balance accounted in the GDP formula

$$GDP_{1,t} = GDP_{1,t-1}\frac{P^d_{1,t-1}Y_{1,t} - P^o_{1,t-1}O^y_{1,t} + P^o_{1,t-1}Y^o_{1,t}}{P^d_{1,t-1}Y_{1,t-1} - P^o_{1,t-1}O^y_{1,t-1} + P^o_{1,t-1}Y^o_{1,t-1}}$$

or less depicted by pronounced negative world supply shocks on the foreign GDP growth (Appendix I, fig.I.5). The contribution of positive world technology shocks counterbalanced by negative world oil efficiency shocks, during the 70s and 80s, is also patent on the shock decomposition plot. Notwithstanding, over the last decade, a contribution of positive world oil efficiency shocks counterbalanced by negative world technology shocks is observed.

Japan

As in the case of U.S. core inflation levels in Japan were higher in the 70s and have been lowered from the beginning of the 80s afterwards (Appendix A, fig.A.4). The shock decomposition of Japanese's core inflation (Appendix I, fig.I.6) is mainly decomposed into positive and negative supply, positive demand and negative monetary shocks. During the 70s positive home technology shocks were, as in case of the U.S., remarkable depicted but any oil supply shocks was observed. The timing when positive supply shocks turned to negative was, however, coincident with oil supply disruptions. Subsequently, we did not identify any direct relation of cause between higher levels of core inflation and oil supply disruptions but only through the supply chain. The results are also compatible with contributions from other endogenous factors as has been suggested by Kilian (2008a) (see section 2.2.2). Moreover, accordingly to results depicted in fig.I.7, positive technology and oil efficieny shocks from the middle 70s to the middle 80s and after 2005, as supply and demand and monetary shocks all over the last four decades are the main shock contributions to Japanese interest rates. The contribution of supply shocks was negative until the 90s and tuned positive ever since. On the contrary demand and monetary shocks had a positive impact on Japan's interest rates until the 90s but turned negative all over the last two decades. For the all period, results (Appendix I, fig.I.7) do suggest a minor impact of monetary shocks on Japanese's interest rates which is in accordance with Kilian (2008a)'s analysis (see subsection 2.2.2) but not with the last two decades of Japanese monetary policy (Ito and Mishkin, 2006). [2] Consequently, the shock decomposition of Japanese's wage inflation is very similar to Japanese's core inflation and previous conclusions from core inflation are also applied to wage inflation. Moreover, we also observe, that Japanese's desired wages are far less susceptible to foreign oil supply shocks than U.S 's desired wages. On the other hand, the everlasting contributions of counterbalanced supply, monetary, home (and world) technology and oil efficiency shocks are observed in Japan's GDP growth shock decomposition (Appendix I, fig.I.9).

[2] Our results using a small matrix computation (Appendix H, fig.I.7) are more in accordance with Kilian (2008a) 's analysis and the last two decades of Japanese monetary policy.)

4.4.2 Exergy efficiency analysis

Behind the definition of useful work, stated in section 2.3, are cumulative technological improvements over time section. Innovation taxonomy characterized a significant number of exergy conversion-to-work efficiency innovations as technology system breaking type or even techno-economic paradigms (Freeman and Perez, 1988). No wonder that the empirical evidence found by Warr et al. (2010), Santos et al. (2014) and Guevara et al. (2014) appointed useful work as being a better candidate as a factor of production (than primary energy) to explain economic growth (Brockway et al., 2015). Among the several structural shocks mapped in the shock decomposition analysis, in the previous section, a clear contribution of home (and foreign) technology and oil efficiency shocks in the deviation of the smoothed value of home (and foreign) GDP growth from its steady state was observed. In this section we demonstrate that the impact of home oil efficiency shocks (our measure of oil efficiency) in oil consumption follows the trajectory of crude oil and petroleum products exergy efficiencies computed by Warr et al. (2010). Accordingly to the author U.S. oil efficiency increased from 1970 to 1972, then decreased until 1984 and increased again until 2000 (Appendix I, fig.I.11). Unfortunately, Warr et al. (2010) didn't publish exergy efficiencies for years after 2000. Figure 4.1, extracted from our model, depicts more or less a negative impact of home oil efficiency (and less pronounced of foreign oil efficiency) on U.S. oil consumption from 1970 to 1972 followed by a positive impact until 1984 and again by a vigorous negative impact until 2000 which is in agreement with the author's observed oil efficiency. On the other side, accordingly to Warr et al. (2010), oil efficiency in Japan has decreased during almost all the three last decades of the XX century (Appendix I, fig.I.10). The only exception was a slightly energy efficiency improvement from 1976 to 1982. Figure 4.2 depicts the shock decomposition of the Japanese's oil consumption. The everlasting negative impact of home oil efficiency shocks on Japanese's oil consumption before 2000 is, however, in total disagreement with the country's constant loss of oil exergy efficiency depicted in fig.I.10. Primary energy supply shifts in Japan (Warr et al., 2010) seems to be a reasonable explanation for the previous incongruity. Moreover, the complete transformation of Japan from an energy-consuming economy to an energy-conserving one (Ohtsu and Imanari, 2002) is also patent in the values of exergy efficiencies (y-axis) of the figures I.10 and I.11 in Appendix I. Unsurprisingly, our results are not so adjustable to aggregate exergy efficiencies computed by Warr et al. (2010) and to the most recently aggregate exergy efficiencies computed by Brockway et al. (2015) until 2010 for the U.S.. This observation is accordingly to our expectations since aggregate and crude oil products efficiencies are significantly different and we only included crude oil and petroleum products as observable variables of energy consumption, energy production and energy prices. On the other hand our shock decomposition plots, fig.I.12

and fig. I.15 in Appendix I, from the U.S. and the Japan's economy, suggest that home and world oil efficiencies shocks had, more than any other shock, an expressive impact in the oil prices of the corresponding economies. It basically means that the changes in oil demand that were not explained by movements in the oil price, due the oil substitution elasticity effect, or movements in a broad measure of economic activity, were highly significant. Noteworthy is

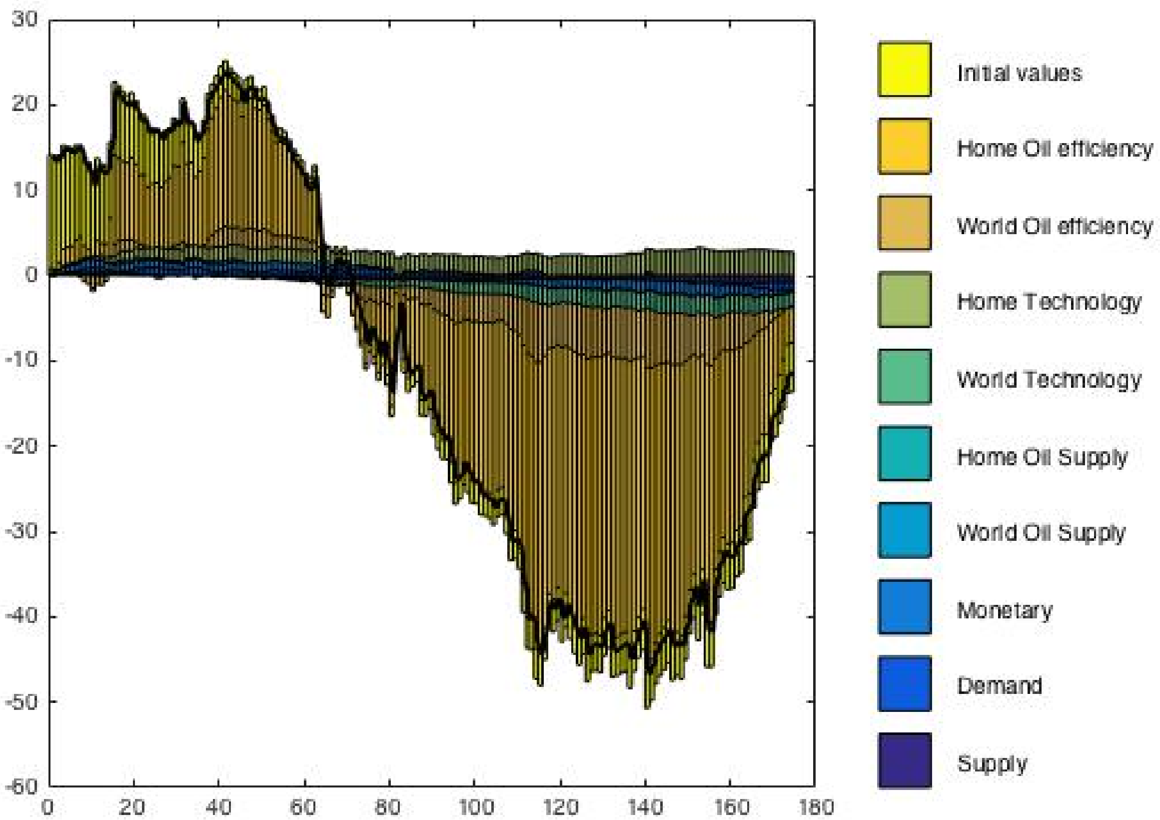

Fig. 4.1 Shock decomposition plot of the U.S. oil consumption. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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also the everlasting and persistent counterbalance impact of home oil efficiency with world oil efficiencies in the U.S. and Japan's oil prices. The oil price's shock decomposition picture of both countries is completed with positive and negative supply, demand, monetary, world technology and world oil supply shocks of lower magnitude. The rise of macroeconomic stability is also patent in both oil prices shock decompositions (figures I.13, I.14, I.16, I.17, in Appendix I) as are depicted less frequent oil shocks, after 1984, already appointed by Nakov and Pescatori (2009) as possible triggers of the "Great Moderation".

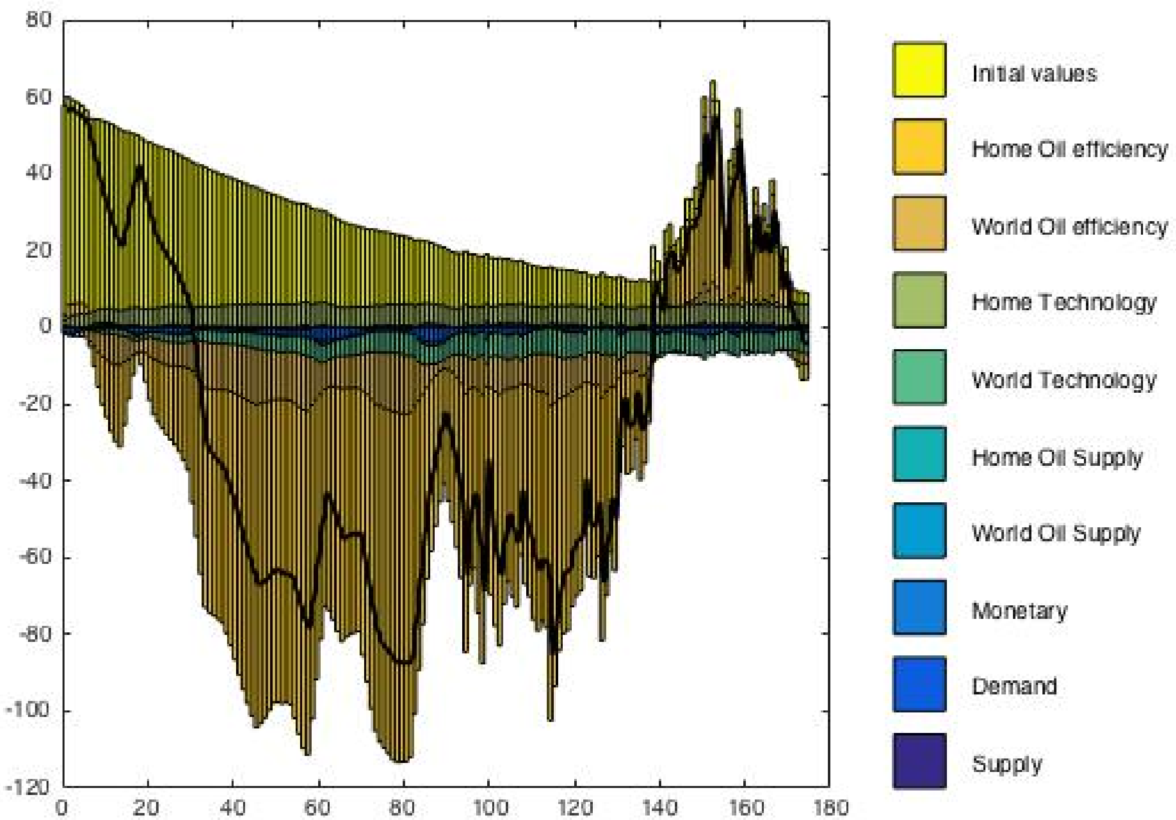

Fig. 4.2 Shock decomposition plot of the Japan oil consumption. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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Chapter 5

Conclusions

This work intended to study the impact of exergy efficiency in economic growth. To address the subject we relied in the analysis of several shock decomposition plots from a macroeconomic model developed by Bodenstein and Guerrieri (2012), which has the particularity to embody inside energy efficiency as technological progress and has been estimated with a Bayesian approach for the economies of U.S. and Japan. After decades of impressive economic growth Japan's economy almost stagnated over the last two decades. Meanwhile the U.S. economy continued to growth although, as in other developed countries, growth rates experienced a gradual desaceleration. Moreover, the trajectories of aggregate exergy efficiencies (and energy intensities) of U.S. and Japan were also very distinct due to the early transformation of Japan from an energy-consuming economy into an energy-conserving one. Notwithstanding, over the last decades, both economies were affected by the same post-WWII oil supply disruptions. Japan's oil efficiency advantage has been appointed by Ohtsu and Imanari (2002) as the cause of a much less severe reduction in Japan's real GDP growth among G7 countries in response to the post-WWII oil supply disruptions. Historical improvements in exergy conversion-to-work efficiency computed by Willians et al. (2008) and Warr et al. (2010) also corroborated this competitive advantage. Behind the definition of useful work, exergy inputs multiplied by an overall conversion efficiency, are cumulative technological improvements over time section. Innovation taxonomy characterized a significant number of exergy conversion-to-work efficiency innovations as technology system breaking type or even techno-economic paradigms (Freeman and Perez, 1988). Not surprisingly, empirical evidence found by Warr et al. (2010), Santos et al. (2014) and Guevara et al. (2014) appointed useful work as being a better candidate as a factor of production (than primary energy) to explain economic growth (Brockway et al., 2015). These authors based their research in Ayres and Warr (2005) who proved that much of the unexplained Solow residual (technological progress) of the U.S. over the last century is almost entirely explained by historical improvements in exergy conversion-to-work efficiency. Notwithstanding since 1975 growth of GDP has, indeed, slightly outstripped the growth of the three main input factors, capital, labor and physical work. In consequence some contribution from 'other' downstream technical improvements has been appointed. One possibility was energy conservation and systems optimization triggered by the energy (exergy) price spike in the 1973–1981 period. The other obvious candidate for this additional value creation was information and communications technologies (ICT) (Ayres and Warr, 2005). The fact is the three factors are not really independent of each other. Increasing exergy conversion efficiency requires investments of capital and labor, while the creation of capital is highly dependent on the productivity of physical work (Ayres and Warr, 2005). For Warr et al. (2010) is not out of question that energy efficiency improvements drived economic growth through a rebound effect. About the subject, however, there are no conclusive answers. The few published time-series studies of useful work accounting have been focused largely on industrialized countries including the US, UK and Japan (e.g. Ayres and Warr (2005) , Willians et al. (2008), Warr et al. (2010)) and later all EU-15 countries (Serrenho et al., 2014) and China (Brockway et al., 2015). What has been found is that, following the case of Japan (Willians et al., 2008), US and UK may no longer be increasing their aggregate exergy efficiency, as increases in process level efficiencies are offset by efficiency dilution taking place (Brockway et al., 2014).

Here we demonstrate that the impact of home oil efficiency shocks in oil consumption, outcomed from our models, follows the trajectory of observed crude oil and petroleum products exergy efficiencies computed by Warr et al. (2010). Our results also suggest that home and world oil efficiencies shocks had over the last decade, more than any other shock, an expressive and everlasting impact in the oil prices of U.S. and Japan economies. Moreover, in both countries, we were able to identify all the post-WWII oil supply disruptions through a reduced positive impact of world oil supply shocks in oil prices. The same impact, however, passed more unnoticed in the shock decomposition plot of Japan's economy, due to higher magnitudes of home (and foreign) oil efficiency shocks, which reinforced the energy-conserving hypothesis appointed by Ohtsu and Imanari (2002). The rise of macroeconomic stability and less frequent oil shocks, appointed by Nakov and Pescatori (2009) as an explanation of the "Great Moderation", were also patent in both oil price shock decompositions after the middle 80s. We additionally found, over the last decades, a non negligible impact of world and home technology shocks in the U.S. and Japan's GDP growth. Observations also corroborated some contribution from 'other' downstream technical improvements not related with energy efficiency technologies, appointed by Warr et al. (2010), after 1975. Moreover, we didn't observe any direct impact of oil supply shocks in the core inflation of U.S. and

Japan. Although, supply chain may have played some role in the proliferation of post-WWII oil supply disruptions through both economies. Accordingly to our results the contribution of other endogenous factors to the 70s high inflation (Kilian, 2008a) is also plausible. A reduction in the intensity of monetary shocks observed, after oil supply disruptions, in U.S. and Japan's interest rates shock decomposition also supported some monetary tightening, appointed by Bernanke et al. (1997), that plausibly affected wages inflation through negative supply shocks. We also observed that Japanese's desired wages were far less susceptible to foreign oil supply shocks than U.S 's desired wages. Subsequently, results have conferred some support to the two main potentially important channels of the transmission of exogenous oil supply shocks, wage rigidities and higher interest rates, appointed by Kilian (2008b). Nonetheless, our shock decompositions also favoured Kilian (2008a)'s hypothesis of a more important contribution of other endogenous factors rather than oil supply shocks to the 70s high inflation levels.

References

Adjemian, S. (2010). Prior distributions in dynare.

Adolfson, M., Laéen, S., Lindé, J., and Villani, M. (2007). Bayesian estimation of an open economy dsge model with incomplete pass-though. *Journal of International Economics*, 72:481–511.

An, S. and Schorfheide, F. (2007a). Bayesian analysis of dsge models. *Econometric Reviews*, 26(2-4):113–172.

An, S. and Schorfheide, F. (2007b). Bayesian analysis of dsge models. *Econometric Reviews*, 26(2-4):113–172.

Andrle, M. (2013a). Undertanding dsge filters in forecasting and policy analysis. *IMF Working Papers*, WP/13/98.

Andrle, M. (2013b). What is in your output gap? unified framework & decomposition into observables. *IMF Working Papers*, WP/13/105.

Ayres, R. (2008). Sustainability economics: Where do we stand? *Ecological Economics*, 67:281–310.

Ayres, R. U. and Warr, B. (2005). Accounting for growth: the role of physical work. *Structural change and economic dynamics*, 16(181-209).

Backus, D. and Crucini, M. (1998). Oil prices and the terms of trade. *Journal of international economics*, 50:185–213.

Barsky, R. B. and Kilian, L. (2001). Do we really know that oil caused the great stagflation? a monetary alternative. *In B.S. Bernanke and K. Rogoff (eds.) NBER Macroeconomics Annual 2001. Cambridge, MA: MIT Press.*

Barsky, R. B. and Kilian, L. (2004). Oil and the macroeconomy since the 1970s. *Journal of Economic Perspectives*, 18(4, Fall):115–134.

Bernanke, B. S., Gertler, M., and Watson, M. W. (1997). Systematic monetary policy and the effects of oil price shocks. *Brookings Papers on Economic Activity*, 1:91–157.

Beyer, A. and Juselius, K. (2010). Does it matter how aggregates are measured? the case of monetary transmission mechanisms in the euro area. *European Central Bank Working Paper Series*, (1149).

Bodenstein, M., Erceg, C., and Guerrieri, L. (2011). Oil shocks and external adjustement. *Journal of international economics*, 83(1):168–184.

Bodenstein, M. and Guerrieri, L. (2011). Appendices to: Oil efficiency, demand, and prices: a tale of ups and downs. Online Publication.

Bodenstein, M. and Guerrieri, L. (2012). Oil efficiency, demand, and prices: a tale of ups and downs. *Society for Economic Dynamics*, 2012 Meeting Papers 25.

Bodenstein, M., Guerrieri, L., and Kilian, L. (2012). Monetary policy responses to oil price fluctuations. *IMF Economic Review*, 60(4):470–504.

Bohi, D. R. (1989). Energy price shocks and macroeconomic performance. *Washington, D. C. Resources for the Future*.

Brockway, P. E., Barrett, J. R., Foxon, T. J., and k. Steiberger, J. (2014). Divergence of trends in us and uk aggregate exergy efficiencies. *Environmental Science & Technology*, 48:9874–9881.

Brockway, P. E., k. Steiberger, J., Barrett, J. R., and Foxon, T. J. (2015). UnderstandingChina' spastandfutureenergydemand:Anexergyefficiencyanddecompositionanalysis. *Applied Energy*, 155:892–903.

Brooks, S. P. and Gelman, A. (1998). General methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics.*, 7:434–455.

Bruno, M. and Sachs, J. (1982). Input price shocks and the slowdown in economic growth: the case of u.k. manufacturing. *Review of Economic Studies*, 49(679-705).

Bruno, M. and Sachs, J. (1985). Economics of worldwide stagflation. *Cambridge, MA: Harvard University Press*.

Buldorini, L., Makrydakis, S., and Thimann, C. (2002). The effective exchange rates of the euro by luca buldorini, stelios makrydakis and christian thimann. *European Central Bank Occasional Paper Series*, 2.

Calvo, G. (1983). Staggered prices in a utility maximizing framework. *Journal of Monetary Economics*, 12:383–398.

Canova, F. (2007). *Methods for Applied Macroeconmic Research*. Princeton University Press.

Chen, C., Ghen, G., and Yao, S. (2012). Do imports crowd out domestic consumption? a comparative study of china, japan and korea. *China Economic Review*, (23):1036–1050.

Chib, S. and Greenberg, E. (1995). Undertanding the metropolis-hastings algorithm. *The American Statistician.*, 49(4):327–335.

Christiano, L. J., Eichenbaum, M., and Evans, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy*, 113(1):1–45.

Christoffel, K., Coenen, G., and Warne, A. (2010). Forecasting with dsge models. *European Central Bank. Working Paper Series*, 1185.

Coenen, G., McAdam, P., and Straub, R. (2008). Tax reform and labor market performance in the euro area: A simulation-based analysis using the new area-wide model. *Journal of Economic Dynamics and Control*, 32(8):2543–2583.

Cooper, J. C. B. (2003). Price elasticity of demand for crude oil: estimates for 23 countries. *Opec Review*, 27(1):1–8.

Crespi, V., Galstyan, A., and Lerman, K. (2008). Top-down vs bottom-up methodologies in multi-agent system design. *Auton. Robots*, 3(24):303–313.

DeJong, D. and Dave, C. (2007). *Structural Macroeconomics*. Princeton University Press.

Edge, R., Kiley, M., and Laforte, J. P. (2009). A comparison of forecast performance between federal reserve staff forecast, simple reduced-form models and a dsge model. *Federal reserve Board of Governors Finance and Economics Discussion Paper Series*.

Fair, C. R. and Taylor, J. B. (1983). Solution and maximum likelihood estimation of dynamic nonlinear rational expectations models. *Econometrica*, 51(4).

Fisher, S. (1977). Long-term contracts, rational expectations and the optimal money. *Journal of Political Economy*, 85(1):191–205.

Flemming, J. (1987). The economics of worldwide stagflation:a review. *Oxford economic papers*, 39:223–232.

Freeman, C. and Perez, C. (1988). *Structural crisis of adjustment, business cycles and investment behaviour*.

Fueki, T., Fukunaga, I., Ichiue, H., and Shirota, T. (2010). Measuring potencial growth with an estimated dsge model of japan's economy. *Bank of Japan Working Paper Series*.

Galí, J. and Blanchard, O. (2010). The macroeconomic effects of oil price shocks: Why are the 2000s so different from the 1970s? *In: Gali, J., Gertler, M.J. (Eds). International Dimensions of Monetary Policy. National Bureau of Economic Research, pp.373-420*, 76.

Gill, J. and King, G. (2004). What to do when your hessian is not invertible. *Sociological Methods & Research*, 33(1):54–87.

Goodfriend, M. and King, R. (1997). The new neoclassical synthesis and the role of monetary policy. *NBER Macroeconomics Annual*.

Griliches, Z. and Jorgenson, W. (1966). Sources of measured productivity change: Capital input. *The American Economic Review*, 1/2:50–61.

Grubler, A. and Messner, S. (1998). Technological change and the timing of mitigation measures. *Energy Economics*, 20:495–512.

Guevara, Z., Sousa, T., and Domingos, T. (2014). An approach for a better evaluation of energy efficiency trends using index decomposition analysis and useful work accounting. *Energy Econ*.

Hamilton, J. D. (2003). What is an oil shock. *Journal of Econometrics*, 113:363–398.

Hamilton, J. D. (2009). Causes and consequences of the oil shock of 2007-2008. *Brookings Papers on Economic Activity. Spring*, pages 215–259.

Hamilton, J. D. (2011). Historical oil shocks. *NBER Working Paper*, (16790).

Hansen, P. L. and Sargent, T. J. (1980). Formulating and estimating dynamic linear rational expectations models. *Journal of Economic Dynamics and Control*, 2:7–46.

Hirose, Y. (2014a). An estimated dsge model with a deflation steady state. *CAMA Working Paper*, 352/2014.

Hirose, Y. (2014b). An estimated dsge model with a deflation steady state: An application to the japanese economy. *CAMA working paper series*.

Hooker, M. (1996). What happened to the oil price-macroeconomy relationship? *Journal of Monetary Economics*, 38:195–213.

Hooker, M. A. (1989). Oil and the macroeconomy when prices go up and down: an extension of hamilton is results. *Quarterly Journal of Economics*, 97(3):740–744.

Hubbard, R. G. (1986). Supply shocks and price adjustment in the world oil market. *Quarterly Journal of Economics*, 101(1):85–102.

Ichiue, H., Kurozumi, T., and Sunakawa, T. (2011). Inflation dynamics and labor market specifications: a bayesian dsge approach for japan's economy. *MPRA Paper No.*, (33391).

Iiboshi, H., Matsumae, T., Namba, R., and Nishiyama, S. (2015). Estimating a dsge model for japan in a data-rich environment. *Journal of The Japanese and International Economics*, 36:25–55.

Iskrev, N. (2011). Evaluating the strength of identification in dsge models. an a priori approach. *Tech. rep. Banco de Portugal*.

Ito, T. and Mishkin, F. S. (2006). Two decades of japanese monetary policy and the deflation problem. *Monetary Policy under Very Low Inflation in the Pacific Rim, NBER-EASE. University of Chicago Press*, 15.

Kilian, L. (2008a). A comparison of the effects of exogenous oil supply shocks on output and inflation in the g7 countries. *Journal of the European Economic Association*, 6(1):78–121.

Kilian, L. (2008b). Exogenous oil supply shocks: How big are they and how much do they matter for the u.s. economy? *Review of Economics and Statistics*, pages 216–240.

Krichene, N. (2002). World crude oil and natural gas: a demand and supply model. *Energy Economics*, 24:557–576.

Kydland, F. E. and Prescott, E. C. (1982). Time to build and aggregate fluctuations. *Econometrica*, 50(1345-1370).

Lanjouw, J. O. and Mody, A. (1996). Innovation and the international diffusion of environmentally responsive technology. *Research Policy*, 25:549–571.

Leduc, S. and Sill, K. (2004). A quantitative analysis of oil-price shocks, systematic monetary policy, and economic downturns. *Journal of Monetary Economics*, 51(4):781–808.

Leduc, S. and Sill, K. (2005). Oil prices, monetary policy, and counterfactual experiments. *Federal Reserve Bank of Cleveland*, (Working Paper No. 0510.).

Lubik, T. A. and Schorfheide, F. (2005). A bayesian look at new open economy macroeconomics. *In: Mark, G., Rogoff, K. eds. NBER Macroeconomics Annual 2005. Cambridge, MA: MIT Press*, pages 313–366.

Nakov, A. and Pescatori, A. (2009). Oil and the great moderation. *The Economic Journal*, 120:131–156.

Negro, M. and Schorfheide, F. (1988). Production, growth, and business cycles: I the basic neoclassic model. *Journal of Monetary Economics*, 21(2-3):195–232.

Negro, M. and Schorfheide, F. (2008). Forming priors for dsge models (and how it affects the assessment of nominal rigidities). *Federal Reserve Bank of New York Staff Reports*, 320.

Negro, M. and Schorfheide, F. (2012). *DSGE Model-Based Forecasting*, volume 2.

Ohanian, L. and Raffo, A. (2011). Aggregate hours worked in oecd countries: New measurement and implications for business cyclesinternational finance discussion papers. board of governors of the federal reserve system. (1039).

Ohtsu, M. and Imanari, T. (2002). *Inside Japanese Business: A Narrative History. 1960-2000*. M. E. Sharpe, Inc., New York.

Peersman, G. and Robays, I. V. (2012). Cross-country differences in the effects of oil shocks. *Energy Economics*, 34:1532–1547.

Pfeifer, J. (2013). A guide to specifying observation equations for the estimation of dsge models. *University of Mannheim*.

Pfeifer, J. (2014). An introduction to graphs in dynare. *University of Mannheim*.

Pina, A. (2012). Supply and demand dynamics in energy systems modeling. *Universidade Técnica de Lisboa. Instituto Superior Técnico. Thesis approved in public session to obtain the PhD Degree in Sustainable Energy Systems*.

Plosser, C. (1989). Understanding real business cycles. *The journal of economic perspevtives*, 3(3):51–77.

Podobnik (2005). Global energy shifts: Fostering sustainability in a turbulent age. *Temple University Press, Philadelphia*.

Popp, D. (2004). Entice: endogenous technological change in the dice model of global warming. *Journal of Environmental Economics and Management*, 48:742–768.

Proença, S. (2013). Impact assessment of energy and climate policies. a hybrid bottom-up general equilibrium model (hybgem) for portugal. *Universidade Técnica de Lisboa. Tese especialmente elaborada para a obtenção do grau de Doutor em Economia*.

Ratto, M. and Iskrev, N. (2011). Identification analysis of dsge models with dynare. https://www.ifk-cfs.de/fileadmin/downloads/events/conferences/monfispol2011/RATTO_IdentifFinal.pdf.

Rotemberg, J. and Woodford, M. (1996). Imperfect competition and the effects of energy price increases on economic activity. *Journal of Money, Credit and Banking*, 28(4):Part 1, 550–77.

Rotemberg, J. and Woodford, M. (1997). An optimization-based econometric framework for the evaluation of monetary policy. *NBER Macroeconomics Annual*, (12).

Ruge-Murcia, F. (2007). Methods to estimate dynamic stochastic general equilibrium models. *Journal of Economic Dynamics and Control*, 53(7):1409–1424.

Ryan, D. L. and Plourde, A. (2002). Smaller and smaller? the price responsiveness of nontransport oil demand. *The Quarterly Review of Economics and Finance*, 42:285–317.

Santos, J., Domingos, T., Sousa, T., and Aubyn, M. (2014). Useful work & economic growth portugal. tcb; 1960-2009.

Schmidt, S. and Wieland, V. (2013). *Handbook of Computable General Equilibrium Modeling*, volume 1. Addison-Wesley.

Serrenho, A., Sousa, T., Warr, B., Ayres, R., and Domingos, T. (2014). Decomposition of useful: the eu(european union) work intensity - 15 countries from 1960 to 2009. *Energy*, 76:704–15.

Serrenho, A., Warr, B., Sousa, T., Ayres, R., and Domingos, T. (2013). Useful work transitions in portugal from 1856 to 2009. *Cambridge Scholars Publishing*.

Smets, F. and Wouters, R. (2003). An estimated dynamics stochastic general equilibrium model of the euro area. *Journal of the European Economic Association*, 1(5):1123–1175.

Smets, F. and Wouters, R. (2007). Shocks and frictions in us business cycles: A bayesian dsge approach. *The American Economic Review*, 97(3).

Smulders, S. and Nooij, M. (2003). The impact of energy conservation on technology and economic growth. *Resource and Energy Economics*, 25:59–79.

Solow, R. (1957). Technical change and the aggregate production function. *Review of economics and Statistics*, 39(3):312–320.

Stefanski, R. (2011). Structural transformation and the oil price. *Review of Economic Dynamics*, 17:484–504. http://www.sciencedirect.com/science/article/pii/S1094202513000525.

Stevens, A. (2013). Analyzing oil demand and supply shocks in an estimated dsge model in applications in dynamic stochastic general equilibrium macroeconomics.

Taylor, J. B. (1980). Aggregate dynamics and staggered contracts. *Journal of Political Economy*, 88(1).

Tovar, C. E. (2008). Dsge models and central banks. *Economics*, 3(2009-16).

Villaverde, J. F. (2010). The econometrics of dsge models. *SERIEs*, 1:3–49.

Warr, B., Ayres, R., Eisenmenger, N., Krausmann, F., and Schandl, H. (2010). Energy use and economic development: A comparative analysis of useful work supply in austria, japan, the united kingdom and the us during 100 years of economic growth. *Ecological Economics*, 69:1904–1917.

Willians, E., Warr, B., and Ayres, R. (2008). Efficiency dilution: Long-term exergy conversion trends in japan. *Environmental Science and Technology*, 42:4964–4970.

Appendix A

Historical Series Plots

A.1 Data Sources

The sources of the previous observed series were the same for the U.S. as for the Japanese economy:

1. the growth of real GDP measured as Millions of national currency, volume estimates, OECD reference year, annual levels, seasonally adjusted (VOBARSA), from OECD Quarterly National accounts, available at http://stats.oecd.org/Index.aspx?DataSetCode=qna.

2. the growth of trade-weighted foreign GDP. The narrow (or broad) weights are from http://www.bis.org/statistics/eer/. Growth of real GDP of OECD countries, measured as VOBARSA, are from OECD Quarterly National accounts, available at http://stats.oecd.org/Index.aspx?DataSetCode=qna. Growth of real GDP of non-OECD countries, measured as constant national currency of each country and seasonally adjusted are from national official statistics. The growth of Euro area (12 countries), previous 1999, was calculated accordingly to Buldorini et al. (2002). The BDH aggregation method was applied in the computation of this composite GDP growth (Beyer and Juselius (2010)). Missing values of some countries series were interpolated by using the proportional Denton method of interpolation. Depending on the country OECD - total GDP growth (VOBARSA), NAFTA GDP Growth (VOBARSA), and Oil Production (measured in dollars) were used as an high-frequency "indicator series". Low-frequency totals were the countries respective annual GDPs at constant local currency published by the World Bank.

3. the log of U.S. real dollar price of oil defined as the U.S. FOB costs of crude oil (dollars per barrel) from the U.S. Energy Information administration (http://www.eia.gov/

dnav/pet/hist/LeafHandler.ashx?n=PET&s=I060000004&f=M
) normalized by the GDP deflator from NIPA Table 1.1.4 (line 1). For the Japanese economy crude oil prices were converted to Yens (http://research.stlouisfed.org/fred2/series/CCUSSP01JPM650N#) and normalized by the Japanese GDP deflator (http://databank.worldbank.org/data/views/reports/tableview.aspx# .[1]

4. the log of U.S. crude oil production was from Table 11.1b of the Monthly Energy Review of the U.S. Energy Information Administration(http://www.eia.gov/totalenergy/data/monthly/). Since for Japan quarterly crude oil production data were not available until 1984 we implemented a mixed frequency approach with annual data from http://www.enecho.meti.go.jp/about/whitepaper/2014html/2-1-3.html and quarterly data from http://www.ieej.or.jp/egeda/database/neworiginal_q_select_cond.php.

5. the growth of foreign annual oil production was from http://don.geddis.org/bets/peakoil/eia-doe-1960-2006.html until the end of 1972. From 1973 onwards quarterly data were from the U.S. Energy Information Administration Table 11.1b World Crude Oil Production: Persian Gulf Nations, Non-OPEC, and World (http://www.eia.gov/totalenergy/data/monthly/).

6. the growth of U.S. and Japan hours worked per capita came from a dataset of quarterly hours worked for 14 OECD countries Ohanian and Raffo (2011).

7. the log of U.S. and Japan BIS effective exchange rate (Narrow indices were used until 1994 and Broad indices afterwards) were from http://www.bis.org/statistics/eer/.

8. the share of private consumption expenditures were from OECD Quarterly National accounts(http://stats.oecd.org/Index.aspx?DataSetCode=qna) for both countries.

9. the U.S. crude oil imports were from the Energy Information Administration (http://tonto.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=MCRIMUS1&f=M). The Japanese imported oil is from 1965 to 1981 are anual data from the BP Statistical review of the world energy 2014 workbook available at http://www.bp.com/en/global/corporate/about-bp/energy-%economics/statistical-review-of-world-energy/statistical-review-downloads.html. Between 1982-1983 we used quarterly data from the U.S. Energy Information administration Table 11.2

[1] I used FOB average values. There is no official Japanese data available. For comparison see the graph Crude Oil CIF and Gasoline Retail Price Trends in Japan in pag.31 from http://www.paj.gr.jp/english/data/paj2013.pdf. Deflator from World Bank only annual data available

Petroleum Consumption in OECD Countries, and from 1984 onwards we use data from Table : Total Oil Net Imports (Thousands Barrels per Day), available at: http://www.eia.gov/cfapps/ipdbproject/iedindex3.cfm?tid=50&pid=76&aid=3&cid=&syid=1982&eyid=2014&freq=Q&unit=TBPD. For each country the price of oil and the real GDP were calculated as described before in order to express crude oil imports as share of GDP .

10. the imports of non petroleum goods expressed as a share of GDP were computed as the quocient between total imports and GDP minus the oil imported share of GDP computed in the previous point. The data were from OECD Quarterly National accounts(http://stats.oecd.org/Index.aspx?DataSetCode=qna) for both countries.

11. the GDP share of export share was from OECD Quarterly National accounts(http://stats.oecd.org/Index.aspx?DataSetCode=qna) for both countries.

12. the GDP share of investment share was from OECD Quarterly National accounts(http://stats.oecd.org/Index.aspx?DataSetCode=qna) for both countries.

13. the core inflation was computed for both countries as the log change in the index of consumer prices - all items non-food, non-energy from the OECD database http://stats.oecd.org/index.aspx?queryid=22519 .

14. the wage inflation (demeaned) was computed as the log difference of the hourly earnings index P data in two subsequent time periods from (http://stats.oecd.org/Index.aspx?DataSetCode=EAR_MEI).

15. the U.S. effective federal funds rate were from Federal Reserve Board (http://www.federalreserve.gov/releases/h15/data.htm). The Japanese Bond rates were from (https://research.stlouisfed.org/fred2/series/INTGSBJPM193N). These annualized net interest rate were divided by four hundred to be transformed into a quarterly net interest rate.

A.2 Historical and Smoothed Variables Plots

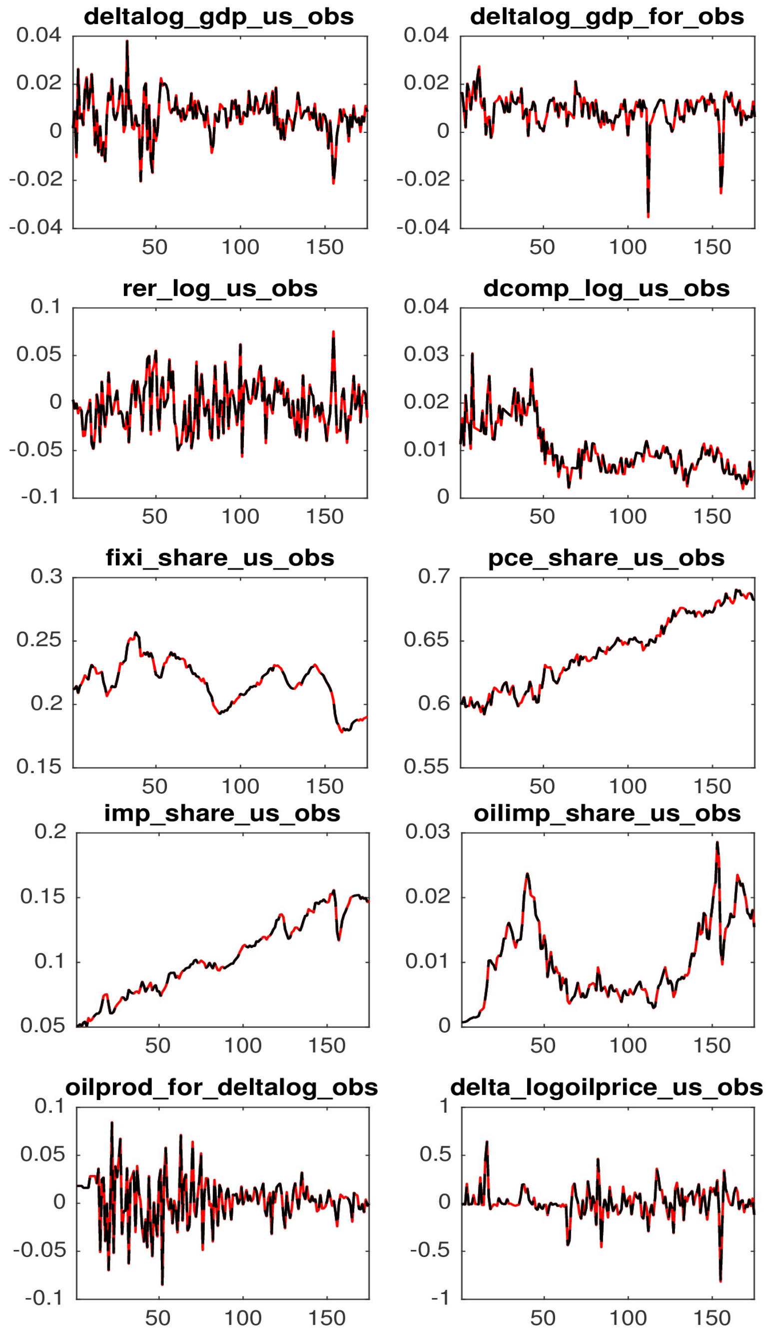

Fig. A.1 Historical and smoothed variables plot of the U.S. The dotted black line depicts the actually observed data, while the red line depicts the estimate of the smoothed variable ("best guess for the observed variable given all observations"), derived from the Kalman smoother at the posterior mean (Bayesian estimation).

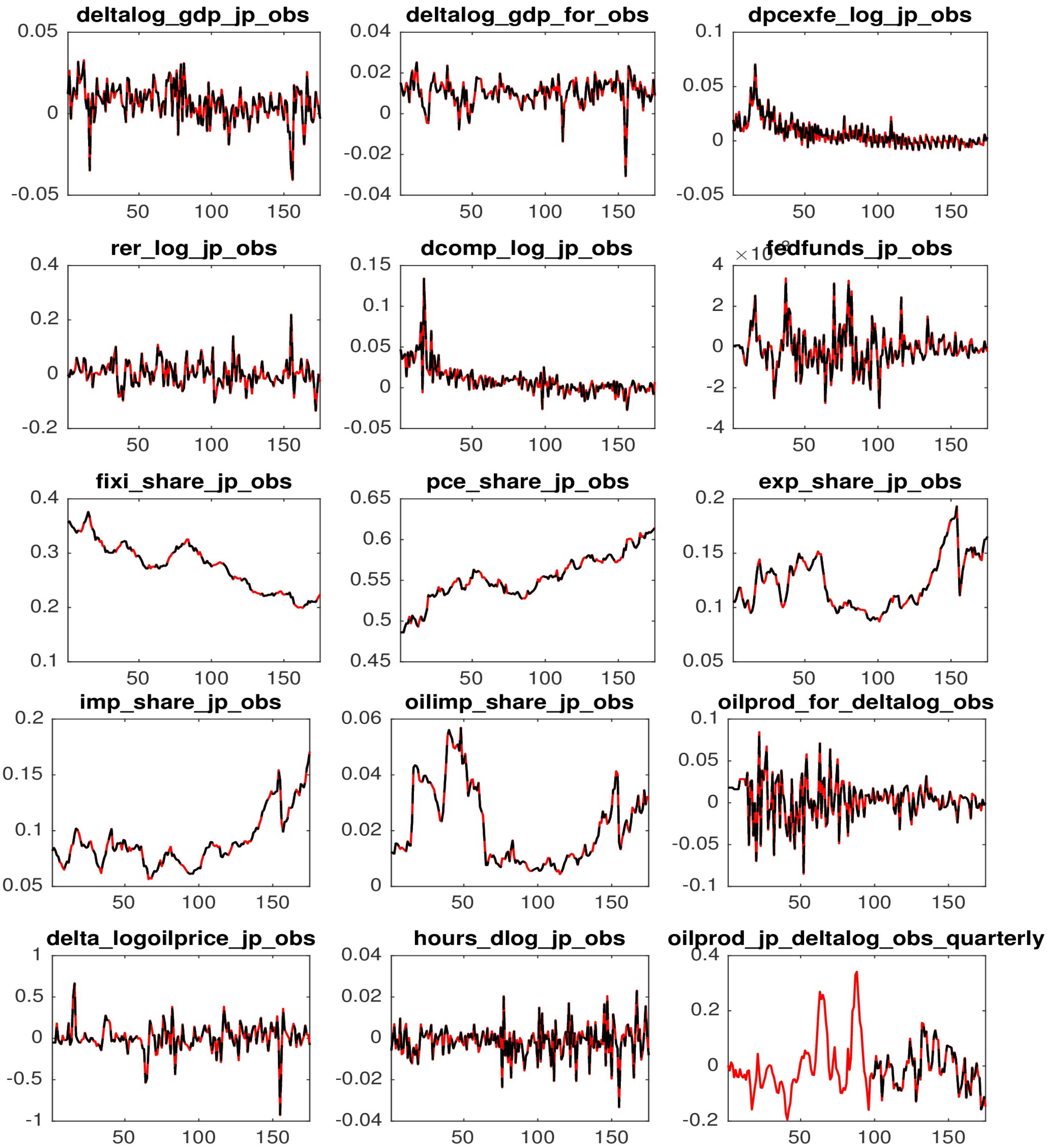

Fig. A.2 Historical and smoothed variables plot of Japan. The dotted black line depicts the actually observed data, while the red line depicts the estimate of the smoothed variable ("best guess for the observed variable given all observations"), derived from the Kalman smoother at the posterior mean (Bayesian estimation).

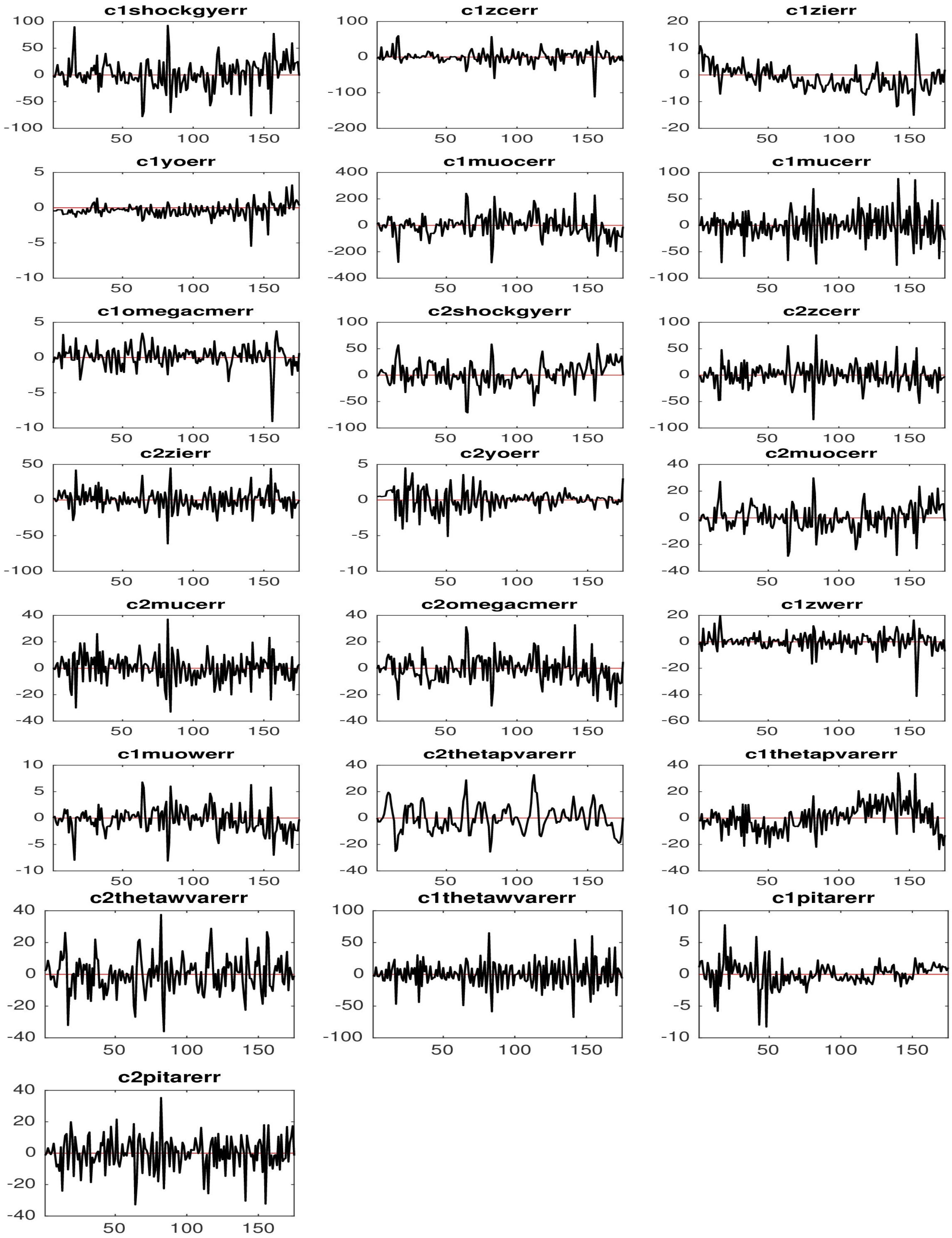

Fig. A.3 Smoothed Shocks plot of the U.S. generated by the estimation when Bayesian estimation is used without the smoother-option. The black line depicts the estimate of the smoothed structural shocks (“best guess for the structural shocks given all observations”), derived from the Kalman smoother at posterior mean (Bayesian estimation).

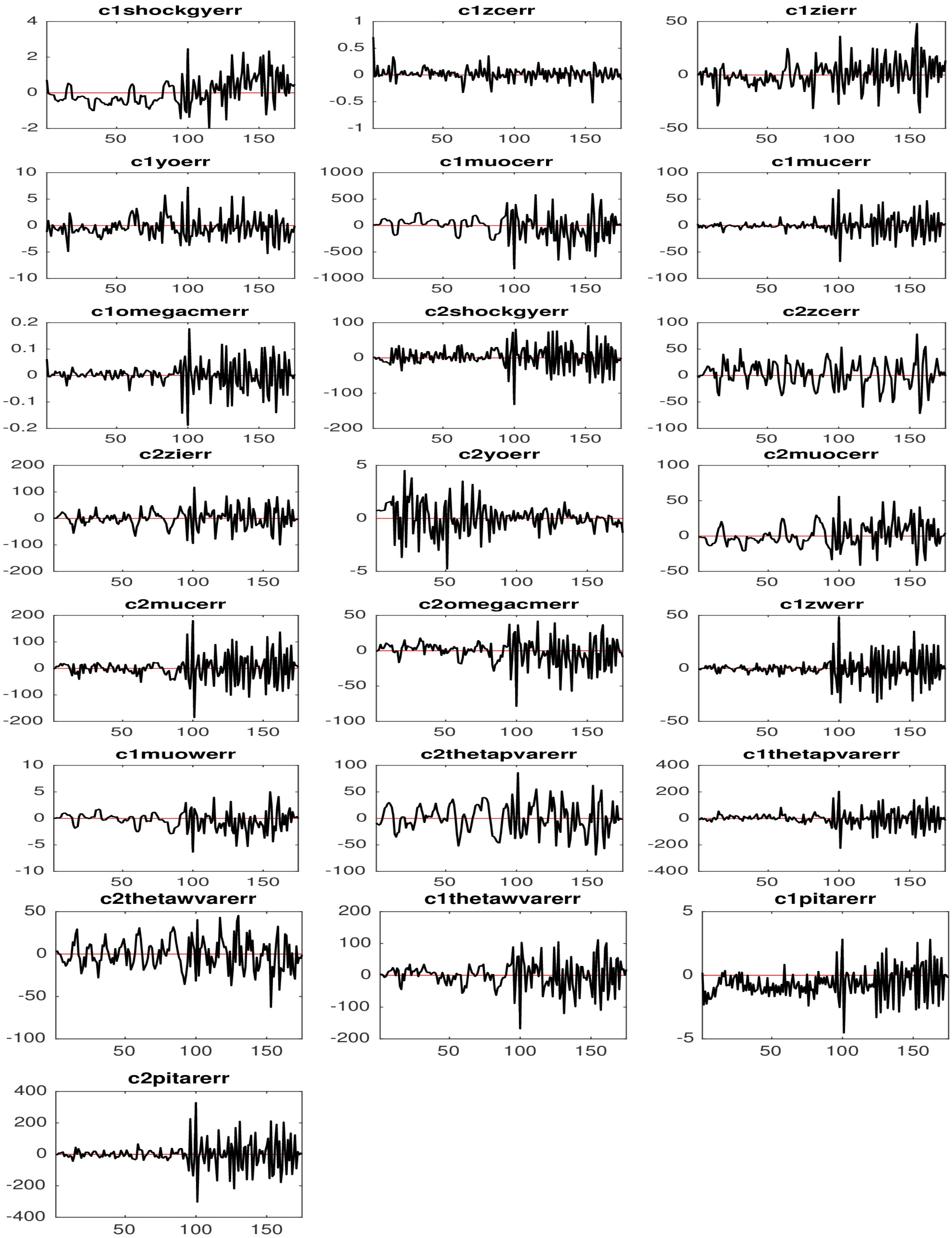

Fig. A.4 Smoothed Shocks plot of Japan generated by the estimation when Bayesian estimation is used without the smoother-option. The black line depicts the estimate of the smoothed structural shocks ("best guess for the structural shocks given all observations"), derived from the Kalman smoother at posterior mean (Bayesian estimation).

Appendix B

Data relation to model-implied variables

As we were dealing with a nonlinear model for Log-Linearization the data were related to model-implied variables by the following measurement equations:

$$
\begin{aligned}
\log\left(\frac{GDP^{obs}_{1,t}}{GDP^{obs}_{1,t-1}}\right) &= \log\left(\frac{P^{d}_{1,t-1}Y_{1,t} - P^{o}_{1,t-1}O^{y}_{1,t} + P^{o}_{1,t-1}Y^{o}_{1,t}}{P^{d}_{1,t-1}Y_{1,t-1} - P^{o}_{1,t-1}O^{y}_{1,t-1} + P^{o}_{1,t-1}Y^{o}_{1,t-1}}\right) + (\mu_{gdp} - 1)\text{[1]} \\
\Pi^{core,obs}_{1,t} &= \Pi^{core}_{1,t}\text{[2]} \\
log(\omega^{obs}_{1,t}) &= log(\omega_{1,t})\text{[3]} \\
r^{s,obs}_{1,t} &= r^{s}_{1,t}\text{[4]} \\
rer^{obs}_{1,t} &= rer_{1,t}\text{[5]} \\
I^{share,obs}_{1,t} &= \frac{P^{i}_{1,t}I_{1,t}}{P^{d}_{1,t}Y_{1,t}}\frac{P^{d}_{1,t}Y_{1,t}}{GDP_{1,t}}\text{[6]} \\
C^{share,obs}_{1,t} &= \frac{P^{c}_{1,t}C_{1,t}}{P^{d}_{1,t}Y_{1,t}}\frac{P^{d}_{1,t}Y_{1,t}}{GDP_{1,t}}\text{[7]} \\
G^{share,obs}_{1,t} &= \frac{P^{c}_{1,t}G_{1,t}}{P^{d}_{1,t}Y_{1,t}}\frac{P^{d}_{1,t}Y_{1,t}}{GDP_{1,t}}\text{[8]} \\
M^{share,obs}_{1,t} &= \frac{P^{d}_{1,t}M_{1,t}}{P^{d}_{1,t}Y_{1,t}}\frac{P^{d}_{1,t}Y_{1,t}}{GDP_{1,t}}\text{[9]} \\
X^{share,obs}_{1,t} &= \frac{P^{d}_{1,t}X_{1,t}}{P^{d}_{1,t}Y_{1,t}}\frac{P^{d}_{1,t}Y_{1,t}}{GDP_{1,t}}\text{[10]}
\end{aligned}
\tag{B.1}
$$

$$
\begin{aligned}
OilM_{1,t}^{share,obs} &= \frac{P_{1,t}^{d}(O_{1,t}-Y_{1,t}^{o})}{P_{1,t}^{d}Y_{1,t}} \frac{P_{1,t}^{d}Y_{1,t}}{GDP_{1,t}}{}^{11} \\
\log\left(\frac{OilProd_{1,t}^{obs}}{OilProd_{1,t-1}^{obs}}\right) &= Y_{1,t}^{o} - Y_{1,t-1}^{o} + (\mu_o - 1)^{12} \\
\log\left(\frac{OilProd_{2,t}^{obs}}{OilProd_{2,t-1}^{obs}}\right) &= Y_{2,t}^{o} - Y_{2,t-1}^{o} + (\mu_o - 1)^{13} \\
\log\left(\frac{Po_{1,t}^{obs}}{Po_{1,t-1}^{obs}}\right) &= \frac{P_{1,t}^{o}}{P_{1,t}^{d}} - \frac{P_{1,t-1}^{o}}{P_{1,t-1}^{d}} + \frac{\mu_{zo}\mu_{gdp,1} - \mu_z}{\mu_z}{}^{14} \\
\log\left(\frac{L_{1,t}^{obs}}{L_{1,t-1}^{obs}}\right) &= L_{1,t} - L_{1,t-1}{}^{15}
\end{aligned}
\tag{B.2}
$$

[1] See definition of GDP using the Laspeyres index, eq. 90 and eq.101 from Bodenstein and Guerrieri (2011) .GDP is not a stationary variable. In order to get rid of the trend we are obliged to work with growth rates. μ_{gdp} is the quarterly gross growth rate of tecnology. For more information see Pfeifer (2013), pag.58

[2]Matched to log levels , for more information see Pfeifer (2013), pag.59. See observation of core price inflation , eq. 115 from Bodenstein and Guerrieri (2012)

[3] $\omega_{1,t}^{obs}$ and $\omega_{1,t}$ respectively are the observed and model gross inflation. For more information see Pfeifer (2013), pag.60

[4]The annualized net inteterest rate were divided by four hundred to be transformed into a quarterly net interest rate. For more information see Pfeifer (2013), pag.60

[5]matched to log levels , for more information see Pfeifer (2013), pag.59. See observation of the real exchange rate, eq. 110 from Bodenstein and Guerrieri (2012)

[6]matched to share levels , for more information see Pfeifer (2013), pag.59. See observation of fixed (investment) share, eq. 113 from Bodenstein and Guerrieri (2012)

[7]matched to share levels , for more information see Pfeifer (2013), pag.59. See observation of consumption share, eq. 111 from Bodenstein and Guerrieri (2012)

[8]matched to share levels , for more information see Pfeifer (2013), pag.59

[9]matched to share levels , for more information see Pfeifer (2013), pag.59. See observation of non-oil import share, eq. 106 from Bodenstein and Guerrieri (2012)

[10]matched to share levels , for more information see Pfeifer (2013), pag.59. See observation of nonoil export share, eq. 108 from Bodenstein and Guerrieri (2012)

[11]matched to share levels , for more information see Pfeifer (2013), pag.59. See observation of oil import share, eq. 103 from Bodenstein and Guerrieri (2012)

[12]Oil Production is not a stationary variable. To get rid of the trend we are obliged to work with growth rates. μ_{gdp} is the quarterly fross growth rate of tecnology. For more information see Pfeifer (2013), pag.58

[13]Oil Production GDP is not a stationary variable. In order to get rid of the trend we are obliged to work with growth rates. μ_{gdp} is the quarterly gross growth rate of oil supply. For more information see Pfeifer (2013), pag.58. see observation equation for oil production, eq. 102 from Bodenstein and Guerrieri (2012)

[14]Oil price is not a stationary variable. In order to get rid of the trend we are obliged to work with growth rates. μ_{gdp} is the quarterly fross growth rate of oil price. For more information see Pfeifer (2013), pag.58. see observation equation for the price of oil, eq. 105 from Bodenstein and Guerrieri (2012)

[15]Using first differences for more information see Pfeifer (2013), pag.60

Appendix C

Bayesian Estimation Parameters

C.1 Prior Distributions Tables

Table C.1 Priors distributions used in the Bayesian estimation of the parameters of the Japanese economy

Parameters	Simb	Dist	Mean	S.D.
JP Trend Depreciation Rate of Capital	μ_3^z	*Normal*	.025	.0002
JP Trend Growth in oil Supply	μ_3^o	*Normal*	1.0026	.15
JP Trend Growth in Technology	μ_3^z	*Normal*	1.0058	.15
JP Labor Supply Elasticity	χ_3	*Normal*	3.5	.000015
JP Habits in Consumption	κ_3	*Beta*	.605	.000001
JP Investment Adjustment Cost	ψ_3^i	*Gamma*	1.24	.00001
JP Trade Subs. Elasticity	ρ_3^c	*Normal*	-10	.00005
JP Oil Subs. Elasticity	ρ_3^o	*Gamma*	-1.73	.00005
JP Capital Subs. Elasticity	ρ_3^k	*Normal*	-2	.00005
JP Calvo Price Parameter	ξ_3^p	*Beta*	.8	.00001
JP Calvo Wage Parameter	ξ_3^w	*Beta*	.7	.00001
JP Policy Rate Smoothing	γ_3^i	*Beta*	.9	.000015
JP Weight on Inflation in M. P. R.	γ_3^π	*Normal*	1.2	.00005
JP Weight on Output Gap in M. P. R.	γ_3^γ	*Beta*	.2	.00001
JP Lagged Wage Indexation	ι_3^p	*Beta*	0.5	.000015
JP Lagged Price Indexation	ι_3^w	*Beta*	0.5	.000015
JP Mon. Policy, AR(1) coef.	ρ_3^π	*Normal*	.4	.000015
JP Mon. Policy, st. dev. of Innov.	σ_3^π	*Normal*	0.057	.00002
				Continued on next page

Table C.1 – continued from previous page

Parameters	Simb	Dist	Mean	S.D.
JP Investment Technology, AR(1) coef.	ρ_3^{zi}	*Normal*	0.97	.0001
JP Investment Technology, st. dev.	σ_3^{zi}	*Normal*	0.023	.00002
JP Gov. Expenditure, AR(1) coef.	ρ_3^{zg}	*Beta*	0.93	.000015
JP Gov. Exp., st. dev. of innov.	σ_3^{zg}	*Normal*	1.52	.0000005
JP Technology, growth AR(1) coef.	ρ_{33}^{z}	*Normal*	0.359	.000015
JP Technology, level error corr. coef.	ρ_{23}^{z}	*Normal*	.0001	.00001
JP Technology, st. dev. of innov.	σ_3^{z}	*Normal*	1.662	.0000002
JP Price Markup, AR(1) coef.	$\rho_3^{\theta p}$	*Beta*	.294	.000015
JP Price Markup, st. dev. of innov.	$\sigma_3^{\theta p}$	*Normal*	.434	.00005
JP Wage Markup, AR(1) coef.	$\rho_3^{\theta w}$	*Normal*	.289	.000015
JP Wage Markup, st. dev. of innov.	$\sigma_3^{\theta w}$	*Normal*	.457	.00005
JP Oil Supply, growth AR(1) coef.	ρ_{33}^{yo}	*Normal*	0.12358	.00003
JP Oil Supply, level error corr. coef.	ρ_{23}^{yo}	*Normal*	.0001	.00005
JP Oil Supply, st. dev. of innov.	σ_3^{yo}	*Normal*	.025	.00002
JP Oil Efficiency, growth AR(1) coef.	ρ_{33}^{zo}	*Normal*	.0001	.000005
JP Oil Efficiency, level error corr. coef.	ρ_{23}^{zo}	*Normal*	.0144	.000009
JP Oil Efficiency, st. dev. of innov.	σ_3^{zo}	*Normal*	.046	.0002
JP Consumption, AR(1) coef.	ρ_3^{zc}	*Beta*	0.96	.000019
JP Consumption, st. dev. of innov.	σ_3^{zc}	*Normal*	4.67	.0000005
JP Import, growth AR(1) coef.	ρ_3^{zm}	*Normal*	.856	.000035
JP Import, level error corr. coef.	ρ_3^{zm}	*Normal*	0.0019	.00004
JP Import, st. dev. of innov.	σ_3^{zm}	*Normal*	3.509	.0000005

Table C.2 Priors distributions used in the Bayesian estimation of the parameters of the Japanese economy

Parameters	Simb	Dist	Mean	S.D.
US Trend Depreciation Rate of Capital	μ_1^{z}	*Normal*	.0337	.02
US Trend Growth in oil Supply	μ_1^{o}	*Normal*	1.0026	.15
US Trend Growth in Technology	μ_1^{z}	*Normal*	1.0058	.15
US Labor Supply Elasticity	χ_1	*Normal*	59.54	.00015

Continued on next page

Table C.2 – continued from previous page

Parameters	Simb	Dist	Mean	S.D.
US Habits in Consumption	κ_1	*Beta*	.65119	.00015
US Investment Adjustment Cost	ψ_1^i	*Gamma*	3.51538	.0001
US Trade Subs. Elasticity	ρ_1^c	*Normal*	1.321	5
US Oil Subs. Elasticity	ρ_1^o	*Gamma*	-1.7316	5
US Capital Subs. Elasticity	ρ_1^k	*Normal*	-2	5
US Calvo Price Parameter	ξ_1^p	*Beta*	.81397	.00015
US Calvo Wage Parameter	ξ_1^w	*Beta*	.88999	.00015
US Policy Rate Smoothing	γ_1^i	*Beta*	.6553386	.00015
US Weight on Inflation in M. P. R.	γ_1^π	*Normal*	.190719	.000005
US Weight on Output Gap in M. P. R.	γ_1^γ	*Beta*	.0000003272	.0001
US Lagged Wage Indexation	ι_1^p	*Beta*	.000000452529	.00025
US Lagged Price Indexation	ι_1^w	*Beta*	.00000032055	.00032
US Mon. Policy, AR(1) coef.	ρ_1^π	*Normal*	.4026116	.0000015
US Mon. Policy, st. dev. of Innov.	σ_1^π	*Normal*	.021694	.0002
US Investment Technology, AR(1) coef.	ρ_1^{zi}	*Normal*	.9059226	.0001
US Investment Technology, st. dev.	σ_1^{zi}	*Normal*	.0268525	.0002
US Gov. Expenditure, AR(1) coef.	ρ_1^{zg}	*Beta*	.99899	.00033
US Gov. Exp., st. dev. of innov.	σ_1^{zg}	*Normal*	.0246	.0002
US Technology, growth AR(1) coef.	ρ_{11}^z	*Normal*	.2162	.00015
US Technology, level error corr. coef.	ρ_{21}^z	*Normal*	.0001	.0001
US Technology, st. dev. of innov.	σ_1^z	*Normal*	.0065559	.00005
US Price Markup, AR(1) coef.	$\rho_1^{\theta p}$	*Beta*	.7401369	.000015
US Price Markup, st. dev. of innov.	$\sigma_1^{\theta p}$	*Normal*	.4773	.00005
US Wage Markup, AR(1) coef.	$\rho_1^{\theta w}$	*Normal*	.9768413	.00015
US Wage Markup, st. dev. of innov.	$\sigma_1^{\theta w}$	*Normal*	3.69878	.0005
US Oil Supply, growth AR(1) coef.	ρ_{11}^{yo}	*Normal*	.1243	.00013
US Oil Supply, level error corr. coef.	ρ_{21}^{yo}	*Normal*	.0001	.00005
US Oil Supply, st. dev. of innov.	σ_1^{yo}	*Normal*	.025349	.0001
US Oil Efficiency, growth AR(1) coef.	ρ_{11}^{zo}	*Normal*	.0001	.00005
US Oil Efficiency, level error corr. coef.	ρ_{21}^{zo}	*Normal*	.0144	.00009
US Oil Efficiency, st. dev. of innov.	σ_1^{zo}	*Normal*	.0476229	.05
US Consumption, AR(1) coef.	ρ_1^{zc}	*Beta*	.918843	.00015
US Consumption, st. dev. of innov.	σ_1^{zc}	*Normal*	.64843349	.0005

Continued on next page

Table C.2 – continued from previous page

Parameters	Simb	Dist	Mean	S.D.
US Import, growth AR(1) coef.	ρ_1^{zm}	*Normal*	.0019	.0004
US Import, level error corr. coef.	ρ_1^{zm}	*Normal*	.026284	.0001
US Import, st. dev. of innov.	σ_1^{zm}	*Normal*	.02684	.05

Table C.3 Priors distributions used in the Bayesian estimation of the parameters of the foreign economy

Parameters	Simb	Dist	Mean	S.D.
US Trend Depreciation Rate of Capital	μ_1^z	*Normal*	.025	.00002
US Trend Growth in oil Supply	μ_1^o	*Normal*	1.0031	.15
US Trend Growth in Technology	μ_1^z	*Normal*	1.0058	.15
For. Labor Supply Elasticity	χ_2	*Normal*	59.5402	.000015
For. Habits in Consumption	κ_2	*Beta*	.65119	.000015
For. Investment Adjustment Cost	ψ_2^i	*Gamma*	3.51538	.00001
For. Trade Subs. Elasticity	ρ_2^c	*Normal*	1.321	.00005
For. Oil Subs. Elasticity	ρ_2^o	*Gamma*	-1.73	.000005
For. Capital Subs. Elasticity	ρ_2^k	*Normal*	-2	.000005
For. Calvo Price Parameter	ξ_2^p	*Beta*	.81397	.000015
For. Calvo Wage Parameter	ξ_2^w	*Beta*	0.88999	.000015
For. Policy Rate Smoothing	γ_2^i	*Beta*	.655338	.000015
For. Weight on Inflation in M. P. R.	γ_2^π	*Normal*	.190719	.00005
For. Weight on Output Gap in M. P. R.	γ_2^y	*Beta*	.00000032	.00001
For. Lagged Wage Indexation	ι_2^p	*Beta*	0.5	.000015
For. Lagged Price Indexation	ι_2^w	*Beta*	0.5	.000015
For. Mon. Policy, AR(1) coef.	ρ_2^π	*Normal*	.5	.000015
For. Mon. Policy, st. dev. of Innov.	σ_2^π	*Normal*	.02169	.00015
For. Investment Technology, AR(1) coef.	ρ_2^{zi}	*Normal*	.9	.00001
For. Investment Technology, st. dev.	σ_2^{zi}	*Normal*	.02685	.00002
For. Gov. Expenditure, AR(1) coef.	ρ_2^{zg}	*Beta*	.99899	.000033
For. Gov. Exp., st. dev. of innov.	σ_2^{zg}	*Normal*	0.024627	.00002
For. Technology, growth AR(1) coef.	ρ_{22}^z	*Normal*	.2162	..000015

Continued on next page

Table C.3 – continued from previous page

Parameters	Simb	Dist	Mean	S.D.
For. Technology, level error corr. coef.	ρ_{21}^{z}	*Normal*	.0001	.0001
For. Technology, st. dev. of innov.	σ_{2}^{z}	*Normal*	.01077	.00005
For. Price Markup, AR(1) coef.	$\rho_{2}^{\theta p}$	*Beta*	.7401369	.000015
For. Price Markup, st. dev. of innov.	$\sigma_{2}^{\theta p}$	*Normal*	.4773	.00005
For. Wage Markup, AR(1) coef.	$\rho_{2}^{\theta w}$	*Normal*	.9768	.00000015
For. Wage Markup, st. dev. of innov.	$\sigma_{2}^{\theta w}$	*Normal*	3.69878	.0000005
For. Oil Supply, growth AR(1) coef.	ρ_{22}^{yo}	*Normal*	.0001	.000013
For. Oil Supply, level error corr. coef.	ρ_{21}^{yo}	*Normal*	.037818	.00005
For. Oil Supply, st. dev. of innov.	σ_{2}^{yo}	*Normal*	.01807229	.00001
For. Oil Efficiency, growth AR(1) coef.	ρ_{22}^{zo}	*Normal*	.0001	.000005
For. Oil Efficiency, level error corr. coef.	ρ_{21}^{zo}	*Normal*	.0144	.000009
For. Oil Efficiency, st. dev. of innov.	σ_{2}^{zo}	*Normal*	.1269187	.00004
For. Consumption, AR(1) coef.	ρ_{2}^{zc}	*Beta*	0.91884	.000015
For. Consumption, st. dev. of innov.	σ_{2}^{zc}	*Normal*	.7174486	.000005
For. Import, growth AR(1) coef.	ρ_{2}^{zm}	*Normal*	.0001	.000009
For. Import, level error corr. coef.	ρ_{2}^{zm}	*Normal*	.0019	.00000994
For. Import, st. dev. of innov.	σ_{2}^{zm}	*Normal*	.041208	.00001
World Technology, growth AR(1) coef.	ρ_{22}^{zw}	*Normal*	0.01	0.5
World Technology, level error corr. coef.	ρ_{21}^{zw}	*Normal*	0.001	0.03
World Technology, st. dev. of innov.	σ_{2}^{zw}	*Normal*	0.001	0.0005
World Oil Efficiency, growth AR(1) coef.	ρ_{22}^{zow}	*Normal*	0.001	0.0015
World Oil Efficiency, level error corr. coef.	ρ_{21}^{zow}	*Normal*	0.001	0.0015
World Oil Efficiency, st. dev. of innov.	σ_{2}^{zow}	*Normal*	0.001	0.0005

C.1.1 Small Indentity Matrix Prior Distribuitions

Table C.4 Priors distributions used in the Bayesian estimation of the parameters of the Japanese economy

Parameters	Simb	Dist	Mean	S.D.
JP Labor Supply Elasticity	χ_3	*Normal*	3.5	15
JP Steady State Growth Oil Supply	μ_3^o	*Normal*	1.0026	.015
JP Steady State Growth Oil Price	μ_3^{zo}	*Normal*	1.003192	0.15
JP Habits in Consumption	κ_3	*Beta*	0.6	0.1
JP Investment Adjustment Cost	ψ_3^i	*Gamma*	1.24	1
JP Trade Subs. Elasticity	ρ^c	*Normal*	-10	5
JP Oil Subs. Elasticity	ρ_3^o	*Gamma*	-1.73	5
JP Capital Subs. Elasticity	ρ_3^k	*Normal*	-2	5
JP Calvo Price Parameter	ξ_3^p	*Beta*	0.81	0.1
JP Calvo Wage Parameter	ξ_3^w	*Beta*	0.7	0.1
JP Sticky Price Parameter	θ_3^p	*Gamma*	0.1	0.05
JP Sticky Price Parameter	θ_3^w	*Gamma*	0.1	0.05
JP Policy Rate Smoothing	γ_3^i	*Beta*	0.9	0.15
JP Weight on Inflation in M. P. R.	γ_3^π	*Normal*	1.2	0.5
JP Weight on Output Gap in M. P. R.	γ_3^y	*Beta*	0.2	0.1
JP Lagged Wage Indexation	ι_3^p	*Beta*	0.5	0.15
JP Lagged Price Indexation	ι_3^w	*Beta*	0.5	0.15
JP Steady state inflation	$\bar{\pi}_3^{core}$	*Normal*	1.006651291	0.09
JP Mon. Policy, AR(1) coef.	ρ_3^π	*Normal*	.4	.15
JP Mon. Policy, st. dev. of Innov.	σ_3^π	*Normal*	0.057	0.02
JP Investment Technology, AR(1) coef.	ρ_3^{zi}	*Normal*	0.97	0.1
JP Investment Technology, st. dev.	σ_3^{zi}	*Normal*	0.023	2
JP Gov. Expenditure, AR(1) coef.	ρ_3^{zg}	*Beta*	0.93	0.15
JP Gov. Exp., st. dev. of innov.	σ_3^{zg}	*Normal*	1.52	5
JP Technology, growth AR(1) coef.	ρ_{33}^z	*Normal*	0.359	0.15
JP Technology, level error corr. coef.	ρ_{23}^z	*Normal*	0.0001	0.001
JP Technology, st. dev. of innov.	σ_3^z	*Normal*	1.662	2
JP Price Markup, AR(1) coef.	$\rho_3^{\theta p}$	*Beta*	0.294	0.15
JP Price Markup, st. dev. of innov.	$\sigma_3^{\theta p}$	*Normal*	0.434	0.5
JP Wage Markup, AR(1) coef.	$\rho_3^{\theta w}$	*Normal*	0.288	0.15

Continued on next page

Table C.4 – continued from previous page

Parameters	Simb	Dist	Mean	S.D.
JP Wage Markup, st. dev. of innov.	$\sigma_3^{\theta w}$	*Normal*	0.4573	5
JP Oil Supply, growth AR(1) coef.	ρ_{33}^{yo}	*Normal*	0.12358342705819	0.3
JP Oil Supply, level error corr. coef.	ρ_{23}^{yo}	*Normal*	0.0001	0.005
JP Oil Supply, st. dev. of innov.	σ_3^{yo}	*Normal*	0.025	0.001
JP Oil Efficiency, growth AR(1) coef.	ρ_{33}^{zo}	*Normal*	0.00010294816003466	0.0005
JP Oil Efficiency, level error corr. coef.	ρ_{23}^{zo}	*Normal*	0.0144	0.09
JP Oil Efficiency, st. dev. of innov.	σ_3^{zo}	*Normal*	0.047022988598085	2
JP Consumption, AR(1) coef.	ρ_3^{zc}	*Beta*	0.96	0.19
JP Consumption, st. dev. of innov.	σ_3^{zc}	*Normal*	4.67	5
JP Import, growth AR(1) coef.	ρ_3^{zm}	*Normal*	0.856	0.35
JP Import, level error corr. coef.	ρ_3^{zm}	*Normal*	0.0019042540938258	0.04
JP Import, st. dev. of innov.	σ_3^{zm}	*Normal*	3.509	5

Table C.5 Priors distributions used in the Bayesian estimation of the parameters of the U.S. economy

Parameters	Simb	Dist	Mean	S.D.
U.S. Labor Supply Elasticity	χ_1	*Normal*	59.54	15
U.S. Steady State Growth Oil Supply	μ_1^o	*Normal*	1.0026	.15
U.S. Steady State Growth Oil Price	μ_1^{zo}	*Normal*	1.003192	0.15
U.S. Habits in Consumption	κ_1	*Beta*	0.6511928096	0.15
U.S. Investment Adjustment Cost	ψ_1^i	*Gamma*	3.5153813918	1
U.S. Trade Subs. Elasticity	ρ_1^c	*Normal*	1.32100396	5
U.S. Oil Subs. Elasticity	ρ_1^o	*Gamma*	-1.7316017	5
U.S. Capital Subs. Elasticity	ρ_1^k	*Normal*	-2	5
U.S. Calvo Price Parameter	ξ_1^p	*Beta*	0.81397044833	0.15
U.S. Calvo Wage Parameter	ξ_1^w	*Beta*	0.8899973220	0.15
U.S. Sticky Price Parameter	θ_1^p	*Gamma*	0.1	0.05
U.S. Sticky Price Parameter	θ_1^w	*Gamma*	0.1	0.05
U.S. Policy Rate Smoothing	γ_1^i	*Beta*	0.6553386077	0.15
U.S. Weight on Inflation in M. P. R.	γ_1^π	*Normal*	0.1907190099	0.5

Continued on next page

Table C.5 – continued from previous page

Parameters	Simb	Dist	Mean	S.D.
U.S. Weight on Output Gap in M. P. R.	γ_1^{γ}	*Beta*	0.0000003272	0.1
U.S. Lagged Wage Indexation	τ_1^{p}	*Beta*	0.00000032055	0.0032
U.S. Lagged Price Indexation	τ_1^{w}	*Beta*	0.000000452529	0.0025
U.S. Steady state inflation	$\bar{\pi}_1^{core}$	*Normal*	1.0113956536	0.1
U.S. Mon. Policy, AR(1) coef.	ρ_1^{π}	*Normal*	0.4026116373	.15
U.S. Mon. Policy, st. dev. of Innov.	σ_1^{π}	*Normal*	0.0216941520	0.2
U.S. Investment Technology, AR(1) coef.	ρ_1^{zi}	*Normal*	0.9059226705	0.1
U.S. Investment Technology, st. dev.	σ_1^{zi}	*Normal*	0.0265	0.2
U.S. Gov. Expenditure, AR(1) coef.	ρ_1^{zg}	*Beta*	0.9989999980	0.33
U.S. Gov. Exp., st. dev. of innov.	σ_1^{zg}	*Normal*	0.0246	0.02
U.S. Technology, growth AR(1) coef.	ρ_{11}^{z}	*Normal*	0.2162	0.15
U.S. Technology, level error corr. coef.	ρ_{21}^{z}	*Normal*	0.00010000024	0.0001
U.S. Technology, st. dev. of innov.	σ_1^{z}	*Normal*	0.0065559859	0.00005
U.S. Price Markup, AR(1) coef.	$\rho_1^{\theta p}$	*Beta*	0.7401369035	0.05
U.S. Price Markup, st. dev. of innov.	$\sigma_1^{\theta p}$	*Normal*	0.4773	0.08
U.S. Wage Markup, AR(1) coef.	$\rho_1^{\theta w}$	*Normal*	0.9768413554	0.15
U.S. Wage Markup, st. dev. of innov.	$\sigma_1^{\theta w}$	*Normal*	3.6987834172	0.2
U.S. Oil Supply, growth AR(1) coef.	ρ_{11}^{yo}	*Normal*	0.1243	0.13
U.S. Oil Supply, level error corr. coef.	ρ_{21}^{yo}	*Normal*	0.0001	0.0005
U.S. Oil Supply, st. dev. of innov.	σ_1^{yo}	*Normal*	0.025	0.001
U.S. Oil Efficiency, growth AR(1) coef.	ρ_{11}^{zo}	*Normal*	0.0001	0.0005
U.S. Oil Efficiency, level error corr. coef.	ρ_{21}^{zo}	*Normal*	0.0144	0.09
U.S. Oil Efficiency, st. dev. of innov.	σ_1^{zo}	*Normal*	0.047	0.05
U.S. Consumption, AR(1) coef.	ρ_1^{zc}	*Beta*	0.9188431675	0.015
U.S. Consumption, st. dev. of innov.	σ_1^{zc}	*Normal*	0.6484334935	0.05
U.S. Import, growth AR(1) coef.	ρ_1^{zm}	*Normal*	0.0001001229	0.009
U.S. Import, level error corr. coef.	ρ_1^{zm}	*Normal*	0.0019	0.04
U.S. Import, st. dev. of innov.	σ_1^{zm}	*Normal*	0.02684	0.01

Table C.6 Priors distributions used in the Bayesian estimation of the parameters of the foreign economy

Parameters	Simb	Dist	Mean	S.D.
For. Labor Supply Elasticity	χ_2	*Normal*	59.540202481992	15
For. Steady State Growth Oil Supply	μ_2^o	*Normal*	1.0026	.15
For. Steady State Growth Oil Price	μ_2^{zo}	*Normal*	1.0058	0.15
For. Habits in Consumption	κ_2	*Beta*	0.65119280966455	0.15
For. Investment Adjustment Cost	ψ_2^i	*Gamma*	3.5153813918585	1
For. Trade Subs. Elasticity	ρ_2^c	*Normal*	1.32100396	5
For. Oil Subs. Elasticity	ρ_2^o	*Gamma*	-1.7316017	5
For. Capital Subs. Elasticity	ρ_2^k	*Normal*	-2	5
For. Calvo Price Parameter	ξ_2^p	*Beta*	0.81397044833069	0.15
For. Calvo Wage Parameter	ξ_2^w	*Beta*	0.88999732204371	0.15
For. Sticky Price Parameter	θ_2^p	*Gamma*	0.1	0.05
For. Sticky Price Parameter	θ_2^w	*Gamma*	0.1	0.05
For. Policy Rate Smoothing	γ_2^i	*Beta*	0.65533860773213	0.15
For. Weight on Inflation in M. P. R.	γ_2^π	*Normal*	0.19071900990448	0.5
For. Weight on Output Gap in M. P. R.	γ_2^y	*Beta*	0.0000003272	0.1
For. Lagged Wage Indexation	ι_2^p	*Beta*	0.81397044833069	0.15
For. Lagged Price Indexation	ι_2^w	*Beta*	0.88999732204371	0.15
For. Mon. Policy, AR(1) coef.	ρ_2^π	*Normal*	.5	.15
For. Mon. Policy, st. dev. of Innov.	σ_2^π	*Normal*	0.021694152070317	0.02
For. Investment Technology, AR(1) coef.	ρ_2^{zi}	*Normal*	0.9	0.1
For. Investment Technology, st. dev.	σ_2^{zi}	*Normal*	0.0265	0.02
For. Gov. Expenditure, AR(1) coef.	ρ_2^{zg}	*Beta*	0.99899999803367	0.33
For. Gov. Exp., st. dev. of innov.	σ_2^{zg}	*Normal*	0.024627248911243	0.05
For. Technology, growth AR(1) coef.	ρ_{22}^z	*Normal*	0.2162	0.015
For. Technology, level error corr. coef.	ρ_{21}^z	*Normal*	0.0001	0.0001
For. Technology, st. dev. of innov.	σ_2^z	*Normal*	0.01077006446931	0.00005
For. Price Markup, AR(1) coef.	$\rho_2^{\theta p}$	*Beta*	0.74013690353831	0.015
For. Price Markup, st. dev. of innov.	$\sigma_2^{\theta p}$	*Normal*	0.4773	0.05
For. Wage Markup, AR(1) coef.	$\rho_2^{\theta w}$	*Normal*	0.97684135541579	0.015
For. Wage Markup, st. dev. of innov.	$\sigma_2^{\theta w}$	*Normal*	3.6987834172965	0.05
For. Oil Supply, growth AR(1) coef.	ρ_{22}^{yo}	*Normal*	0.0001	0.13

Continued on next page

Table C.6 – continued from previous page

Parameters	Simb	Dist	Mean	S.D.
For. Oil Supply, level error corr. coef.	ρ_{21}^{yo}	*Normal*	0.037818500221807	0.0005
For. Oil Supply, st. dev. of innov.	σ_{2}^{yo}	*Normal*	0.018072294073071	0.0001
For. Oil Efficiency, growth AR(1) coef.	ρ_{22}^{zo}	*Normal*	0.0001	0.0005
For. Oil Efficiency, level error corr. coef.	ρ_{21}^{zo}	*Normal*	0.0144	0.09
For. Oil Efficiency, st. dev. of innov.	σ_{2}^{zo}	*Normal*	0.12691876301873	0.04
For. Consumption, AR(1) coef.	ρ_{2}^{zc}	*Beta*	0.91884316757498	0.015
For. Consumption, st. dev. of innov.	σ_{2}^{zc}	*Normal*	0.71744864960161	0.05
For. Import, growth AR(1) coef.	ρ_{2}^{zm}	*Normal*	0.0001	0.009
For. Import, level error corr. coef.	ρ_{2}^{zm}	*Normal*	0.0019	0.04
For. Import, st. dev. of innov.	σ_{2}^{zm}	*Normal*	0.041208515408324	0.01
For. Technology, growth AR(1) coef.	ρ_{22}^{z}	*Normal*	0.01	0.5
For. Technology, level error corr. coef.	ρ_{21}^{z}	*Normal*	0.001	0.03
For. Technology, st. dev. of innov.	σ_{2}^{z}	*Normal*	0.001	0.0005
For. Oil Efficiency, growth AR(1) coef.	ρ_{22}^{zo}	*Normal*	0.001	0.0015
For. Oil Efficiency, level error corr. coef.	ρ_{21}^{zo}	*Normal*	0.001	0.0015
For. Oil Efficiency, st. dev. of innov.	σ_{2}^{zo}	*Normal*	0.001	0.0005
World Technology, growth AR(1) coef.	ρ_{22}^{zw}	*Normal*	0.01	0.5
World Technology, level error corr. coef.	ρ_{21}^{zw}	*Normal*	0.001	0.03
World Technology, st. dev. of innov.	σ_{2}^{zw}	*Normal*	0.001	0.0005
World Oil Efficiency, growth AR(1) coef.	ρ_{22}^{zow}	*Normal*	0.001	0.0015
World Oil Efficiency, level error corr. coef.	ρ_{21}^{zow}	*Normal*	0.001	0.0015
World Oil Efficiency, st. dev. of innov.	σ_{2}^{zow}	*Normal*	0.001	0.0005

C.2 Prior and Posterior Distributions Plots


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c1vkappa
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c1rhoc
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c1rhov
c1chi
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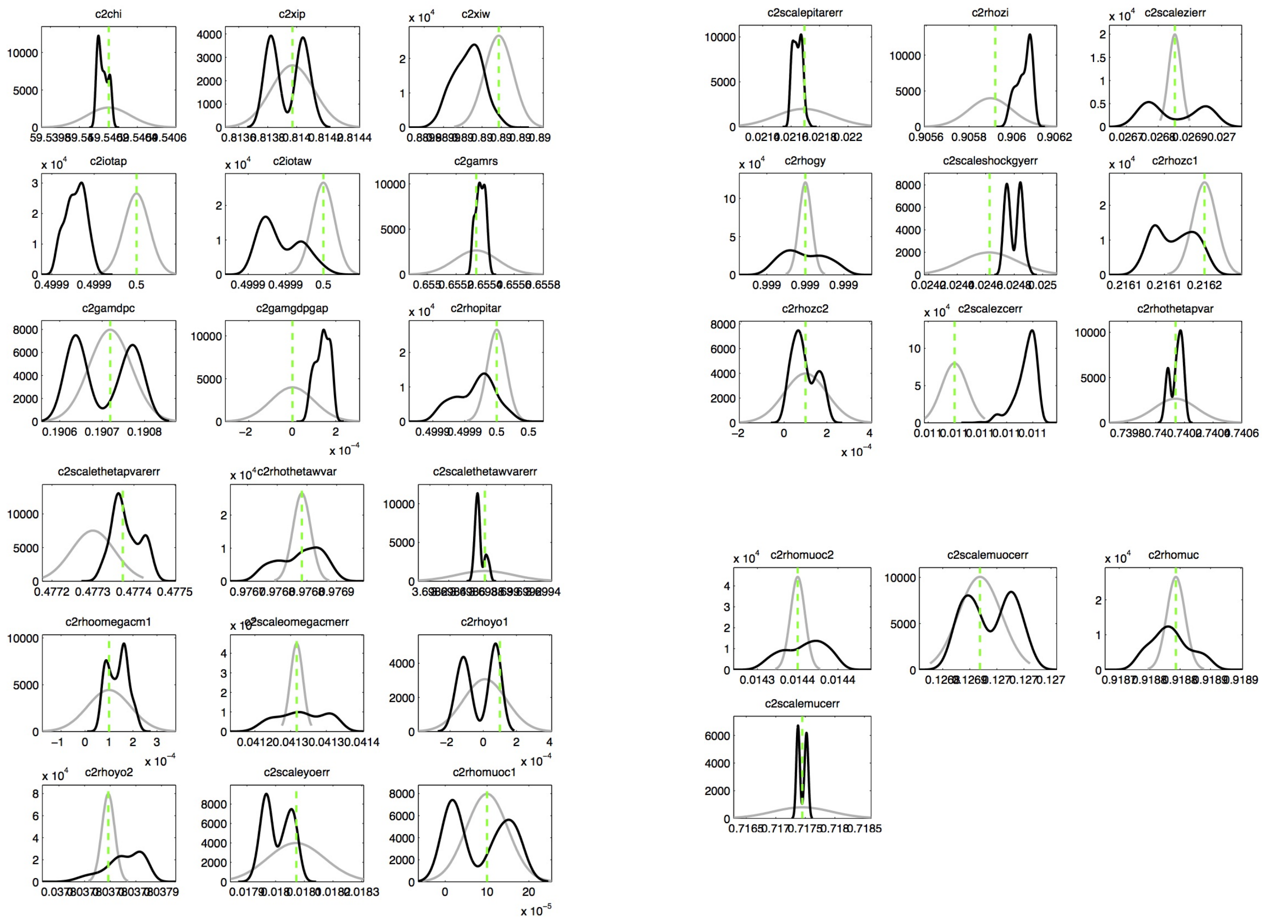
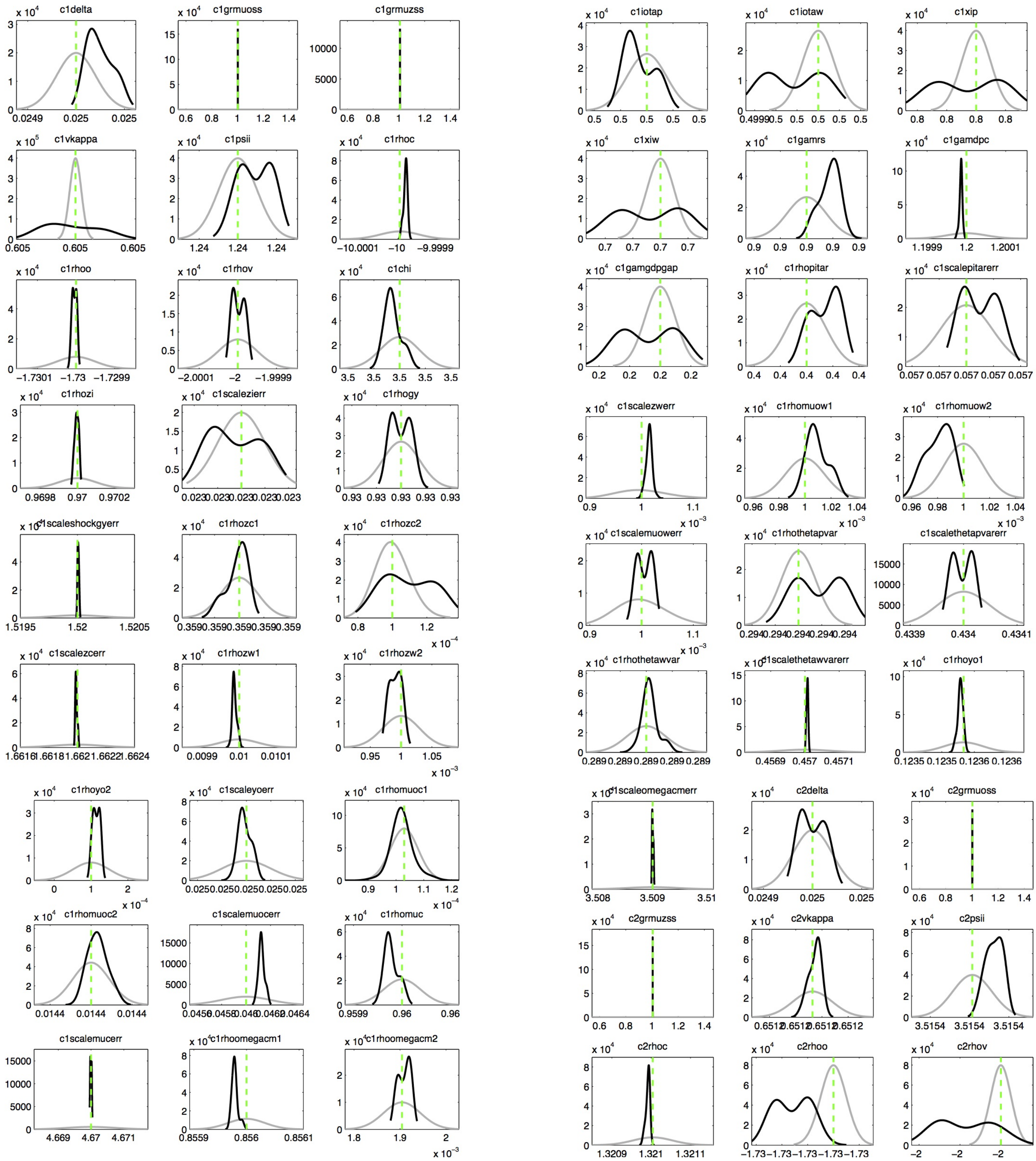


Fig. C.2 Prior and Posterior Distributions. U.S model's bayesian estimation.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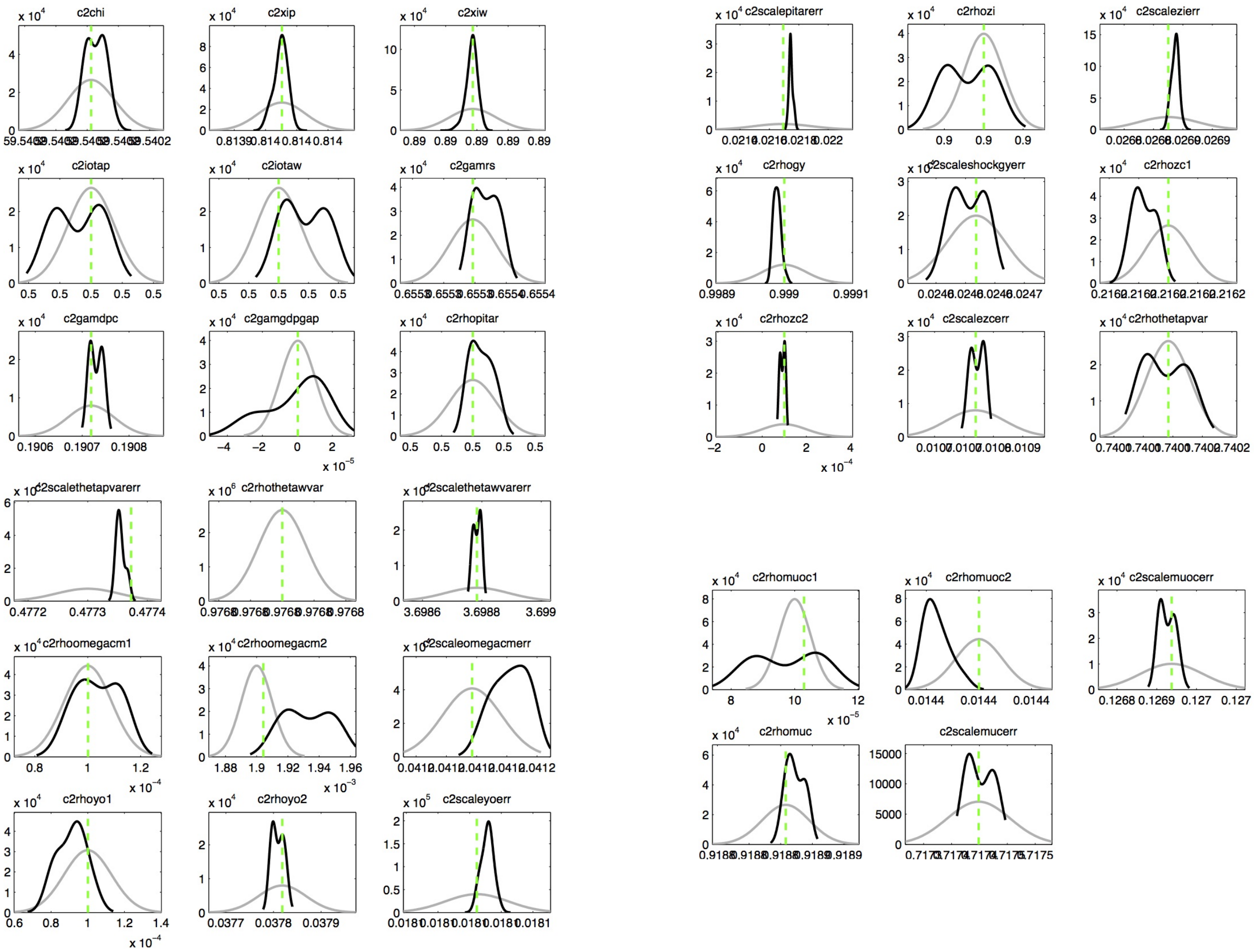
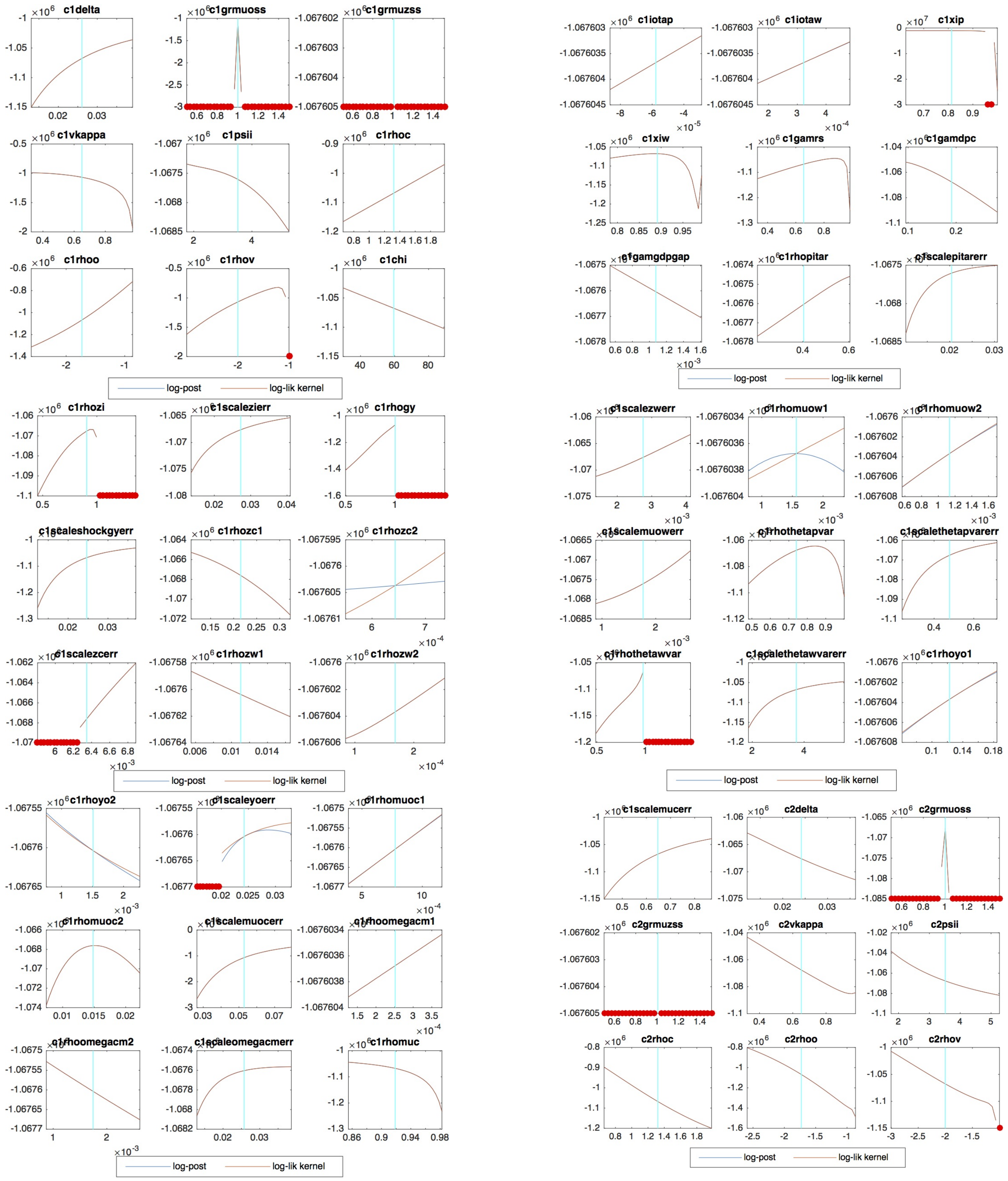


Fig. C.4 Prior and Posterior Distributions. Japan model's bayesian estimation.

Appendix D

Check Mode Output

The mode check plots generated by the mode_check option of the Dynare estimation-command is the appropriate tool to check whether the mode-computation found the (local) mode. The plot output displays an interval of parameter values (x-axis) centered around the estimated mode (horizontal magenta line) and the corresponding value of the log-likelihood kernel (y-axis) shifted up or down by the prior value at the posterior mode (green line) and of the posterior likelihood function (blue line). The plots also show the influence that differences in the shape between the likelihood kernel and the posterior likelihood have on the curvature of the likelihood fluctuation. Ideally, the estimated mode should be at the maximum of the posterior likelihood (Pfeifer, 2014).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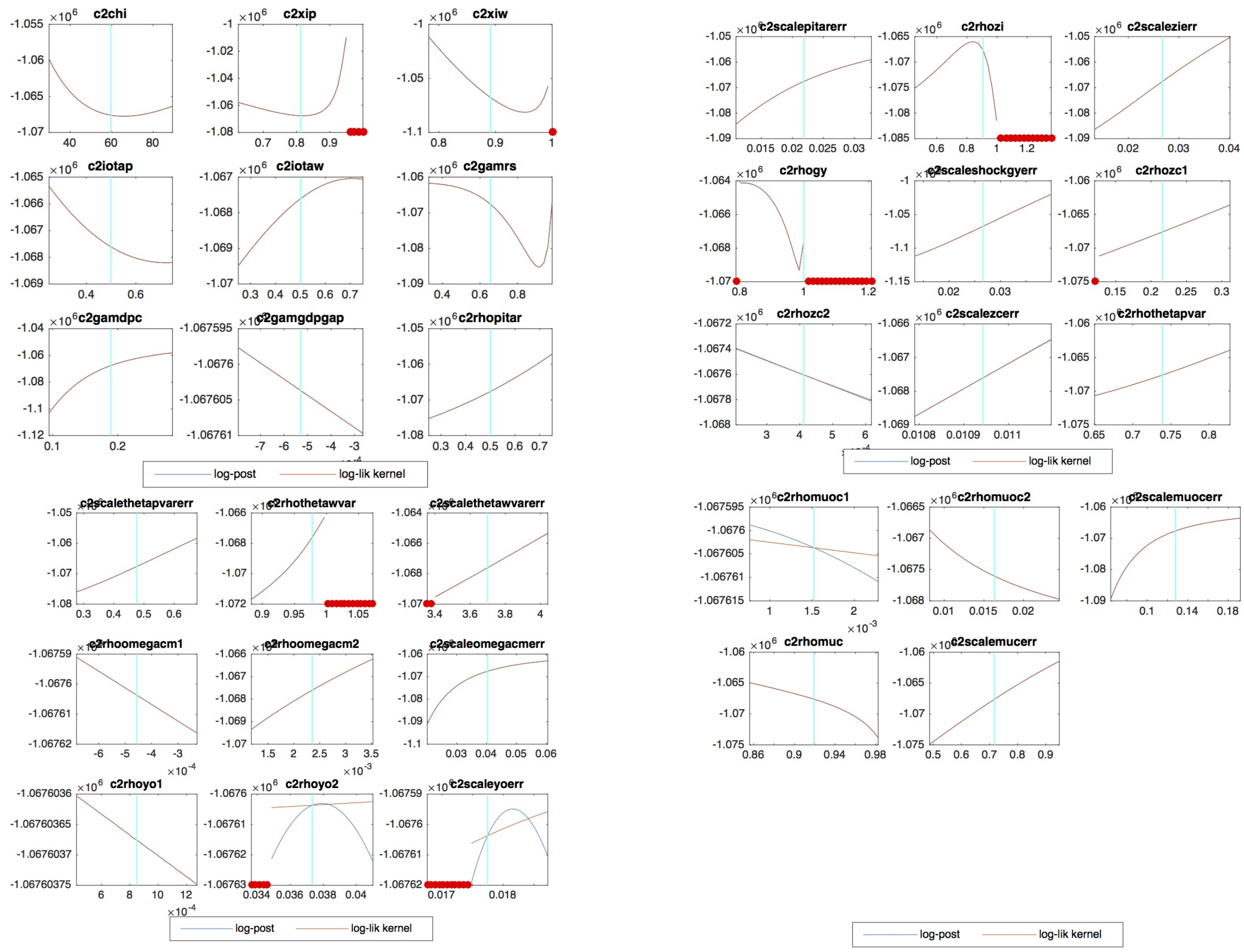
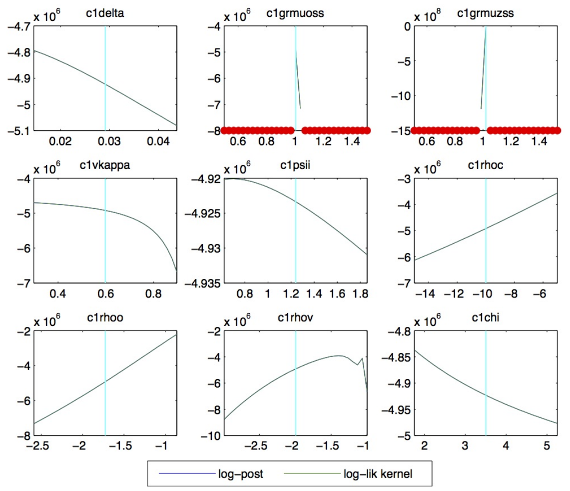


Fig. D.2 Check Mode Plots from the U.S. model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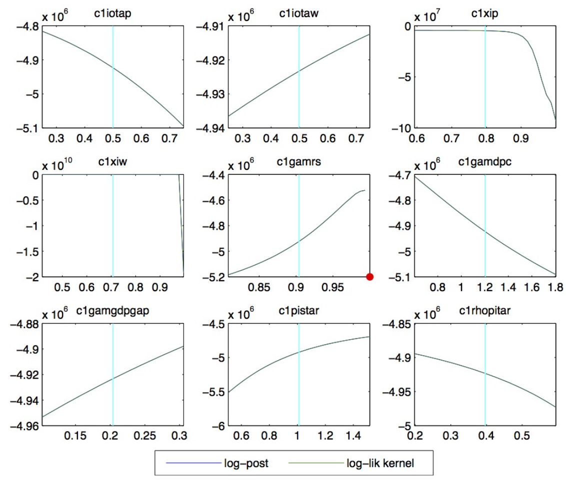
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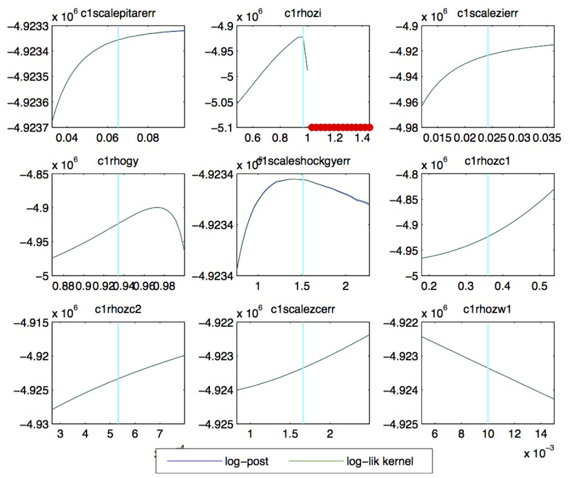
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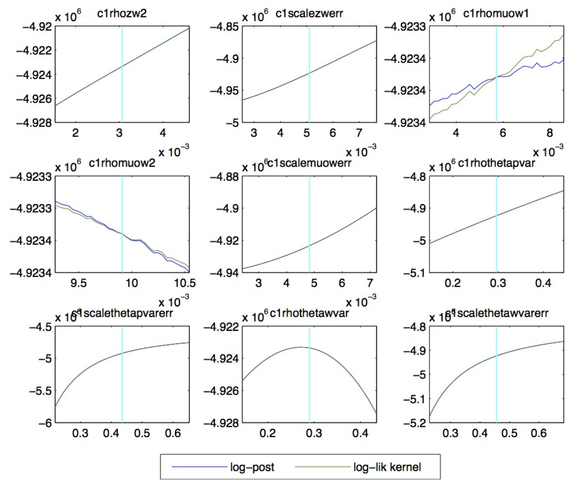
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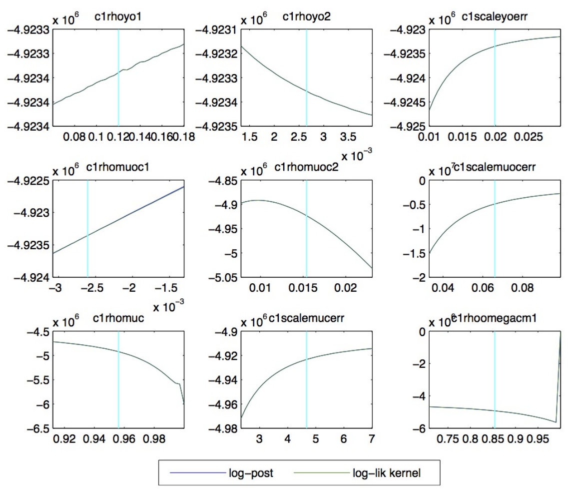
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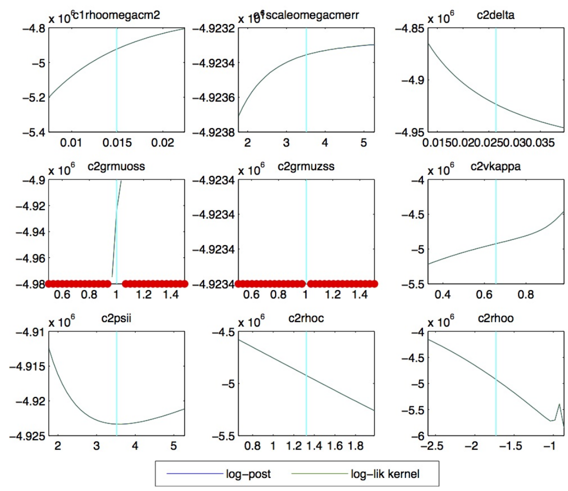
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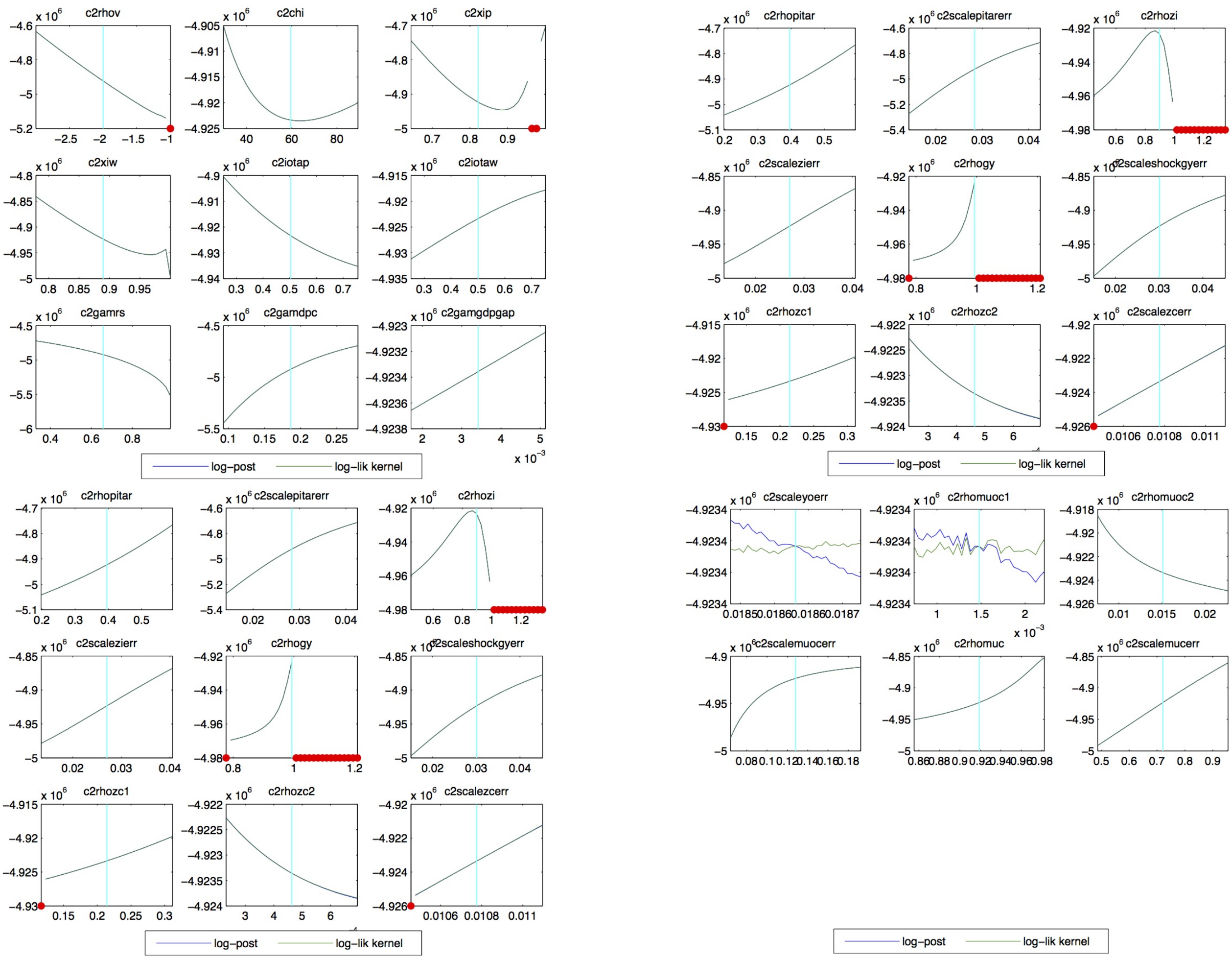

Fig. D.4 Check Mode Plots from the Japan model

Appendix E

Convergence Diagnostics Plots

The Monte Carlo Markov Chain (MCMC) univariate diagnostics based on Brooks and Gelman (1998) and the Multivariate convergence diagnostic (which does not follow Brooks and Gelman (1998) strictly) are automatically generated by Dynare's estimation command if [mh replic] is larger than 2000 and if option [nodiagnostic] is not used. The univariate convergence diagnostics is based on comparing pooled and within MCMC moments (Dynare displays the second and third order moments, and the length of the Highest Probability Density interval covering 80% of the posterior distribution). The multivariate diagnostics is the same as the univariate except for the statistics that are based on the range of the posterior likelihood function instead of the individual parameters. Thus, the posterior kernel is used to aggregate the parameters. Figures E.3 and E.4 are respectively from our U.S and Japan models. They represent the Monte Carlo Markov Chain (MCMC) univariate diagnostics for ρ_{11}^{zc}, ρ_{12}^{zc}, σ_{2}^{zc}, ρ_{11}^{zc}, ρ_{12}^{zc}, σ_{1}^{zc} parameters. The first column with the appended (Interval) represented inside, from both figures, shows the Brooks and Gelman (1998) (Section 3) convergence multivariate diagnostics for the 80% interval. The blue line shows the 80% interval/quantile range based on the pooled draws from all sequences. The mean interval range based on the draws of the individual sequences is, on the other side, depicted in the red line. The second and third column with the appended (m2) and (m3) show an estimate of the same statistics for the second and third central moments. The superposition and horizontal stabilization of both lines (red and blue) demonstrates that the convergence of the chains has already been reached. Additionally, the Multivariate convergence diagnostic for the U.S. and Japan models is, respectively, depict in figure E.1 and E.2. Again, convergence is indicated when the two lines remain close to each other and stabilize. In our case we do observe the superposition and horizontal stabilization of both lines for approx. the U.S. and Japan 150000 draws diagnostic.

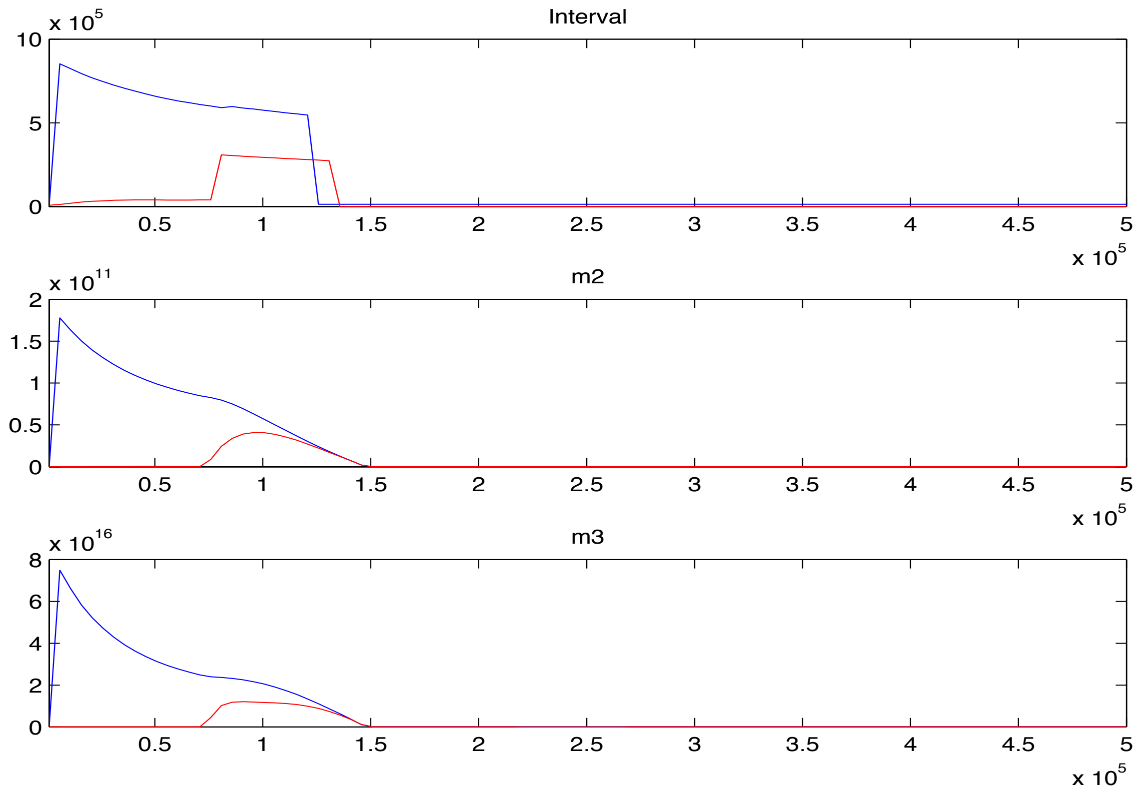

Fig. E.1 Multivariate convergence diagnostics of the U.S. model generated by the estimation-command. This diagnostics is the same as the univariate one depicted in Figure E.3, except for the statistics now being based on the range of the posterior likelihood function instead of the individual parameters. Thus, the posterior kernel is used to aggregate the parameters. Again, convergence is indicated by the two lines stabilizing and being close to each other. The x-axis displays the number of draws, while the y-axis displays part of the support of the prior distribution (Pfeifer, 2014).

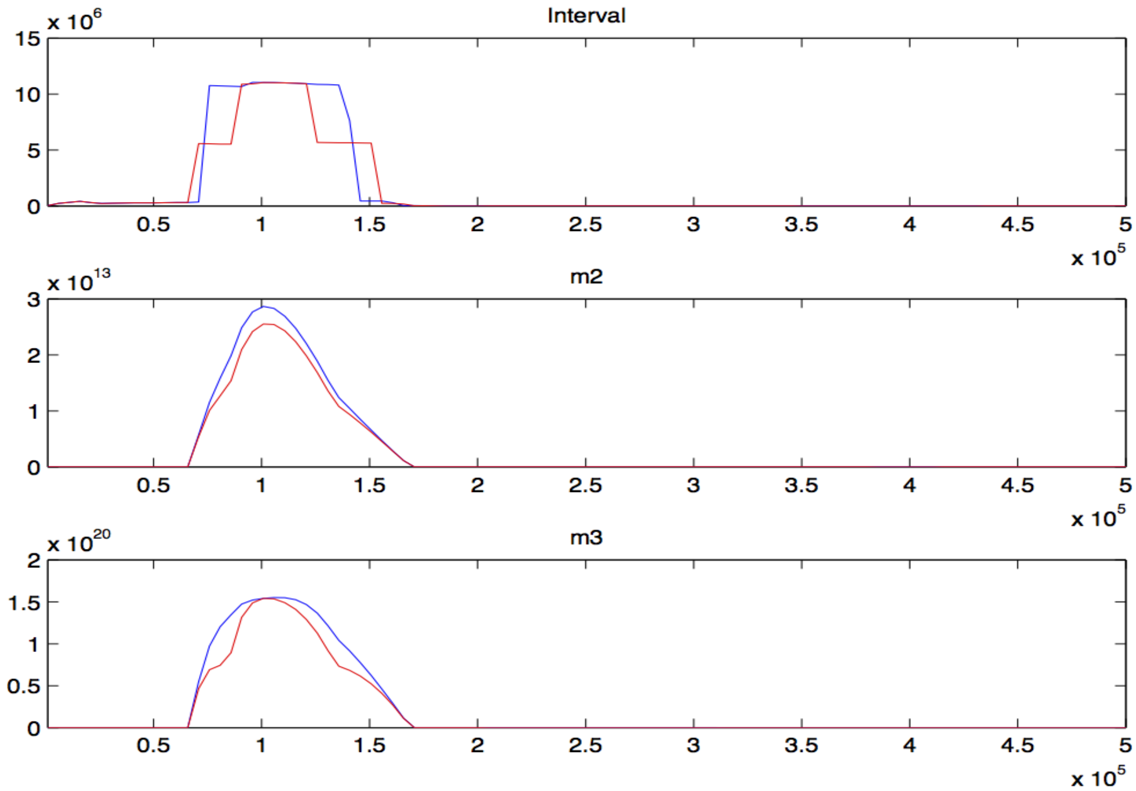

Fig. E.2 Multivariate convergence diagnostics of Japan model generated by the estimation-command. This diagnostics is the same as the univariate one depicted in Figure E.4, except for the statistics now being based on the range of the posterior likelihood function instead of the individual parameters. Thus, the posterior kernel is used to aggregate the parameters. Again, convergence is indicated by the two lines stabilizing and being close to each other. The x-axis displays the number of draws, while the y-axis displays part of the support of the prior distribution (Pfeifer, 2014).

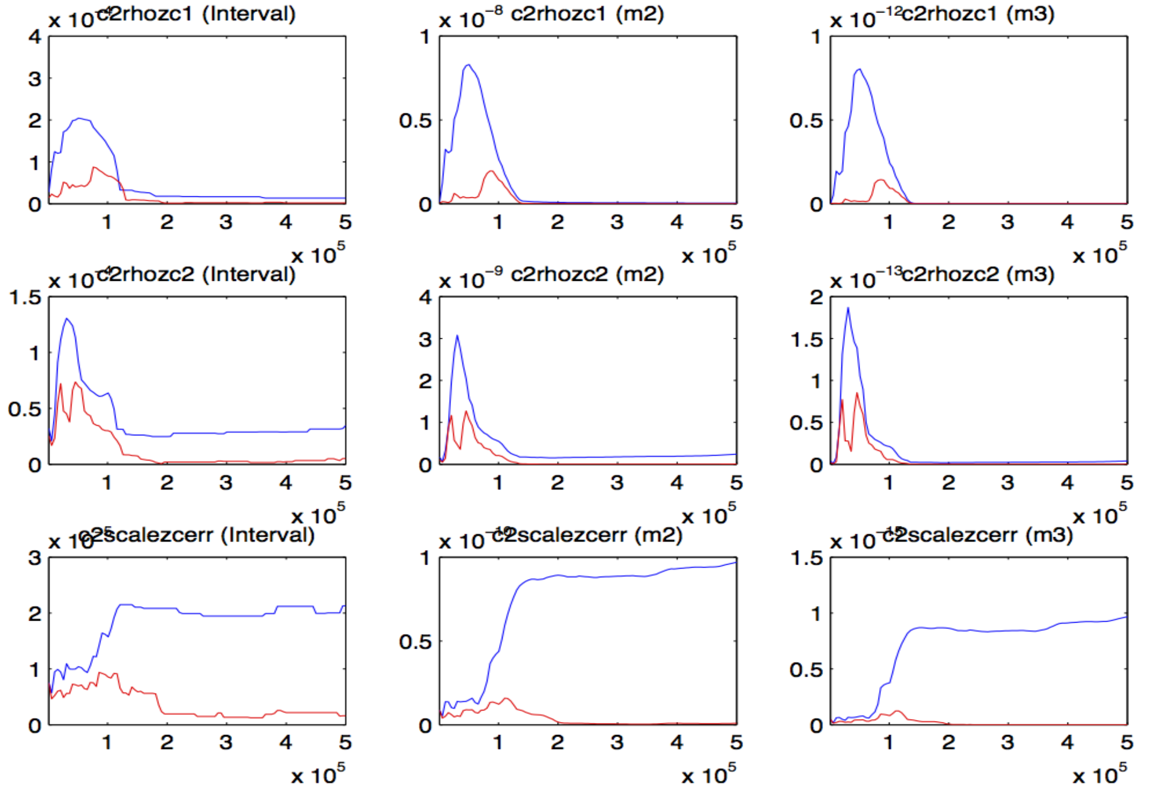

Fig. E.3 Monte Carlo Markov Chain (MCMC) univariate diagnostics (Brooks and Gelman (1998)) generated by the estimation-command if `mh_nblocks` is larger than 1 and `mh_replic` larger than 2000 for ρ_{21}^{zc}, ρ_{22}^{zc}, σ_2^{zc} parameters of the U.S. model. The first column with the appended (Interval) shows the Brooks and Gelman (1998) convergence diagnostics for the 80% interval.The blue line shows the 80% interval/quantile range based on the pooled draws from all sequences, while the red line shows the mean interval range based on the draws of the individual sequences. The second and third column with the appended (m2) and (m3) show an estimate of the same statistics for the second and third central moments, i.e. the squared and cubed absolute deviations from the pooled and the within-sample mean, respectively. If the chains have converged, the two lines should stabilize horizontally and should be close to each other.The depicted graphs are based on an increasing number of parameter draws. The x-axis displays the number of draws, while the y-axis displays part of the support of the prior distribution (Pfeifer, 2014).

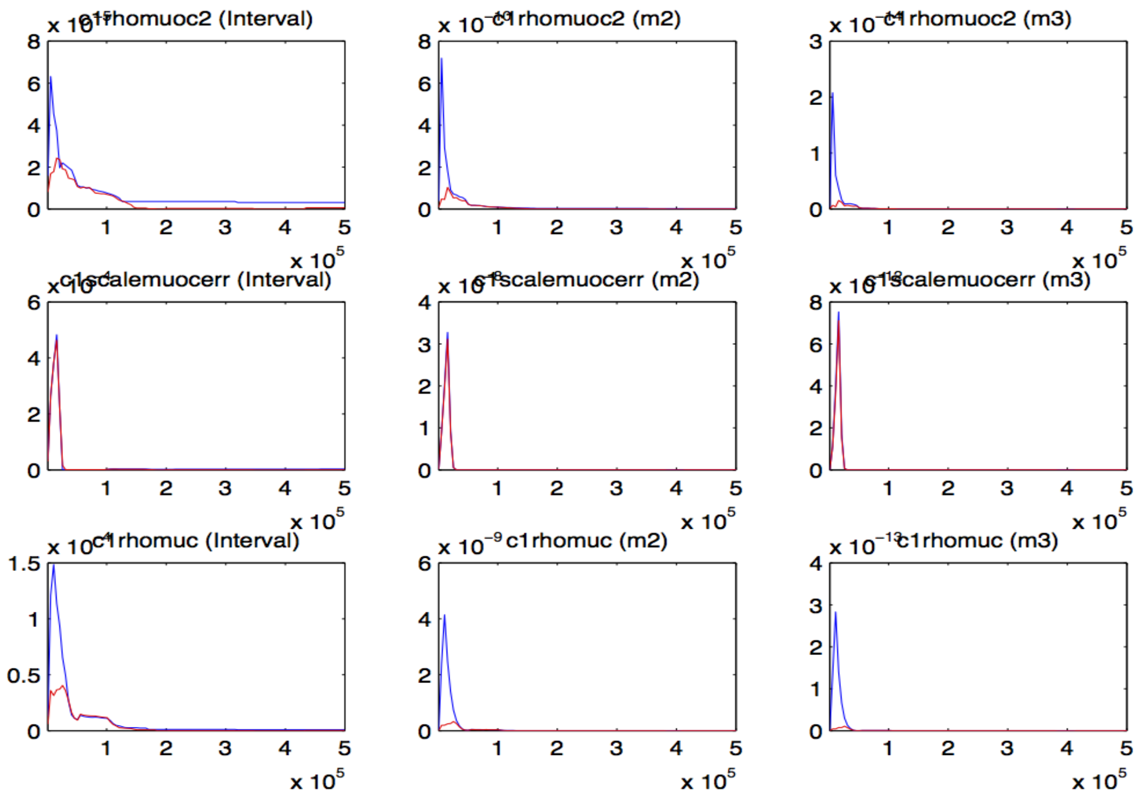

Fig. E.4 Monte Carlo Markov Chain (MCMC) univariate diagnostics (Brooks and Gelman (1998)) generated by the estimation-command if `mh_nblocks` is larger than 1 and `mh_replic` larger than 2000 for ρ^{zc}_{11}, ρ^{zc}_{12}, σ^{zc}_{1}, parameter of the Japan model. The first column with the appended (Interval) shows the Brooks and Gelman (1998) convergence diagnostics for the 80% interval.The blue line shows the 80% interval/quantile range based on the pooled draws from all sequences, while the red line shows the mean interval range based on the draws of the individual sequences. The second and third column with the appended (m2) and (m3) show an estimate of the same statistics for the second and third central moments, i.e. the squared and cubed absolute deviations from the pooled and the within-sample mean, respectively. If the chains have converged, the two lines should stabilize horizontally and should be close to each other.The depicted graphs are based on an increasing number of parameter draws. The x-axis displays the number of draws, while the y-axis displays part of the support of the prior distribution(Pfeifer, 2014).

Appendix F

Identification and Sensitivity Analysis Plots

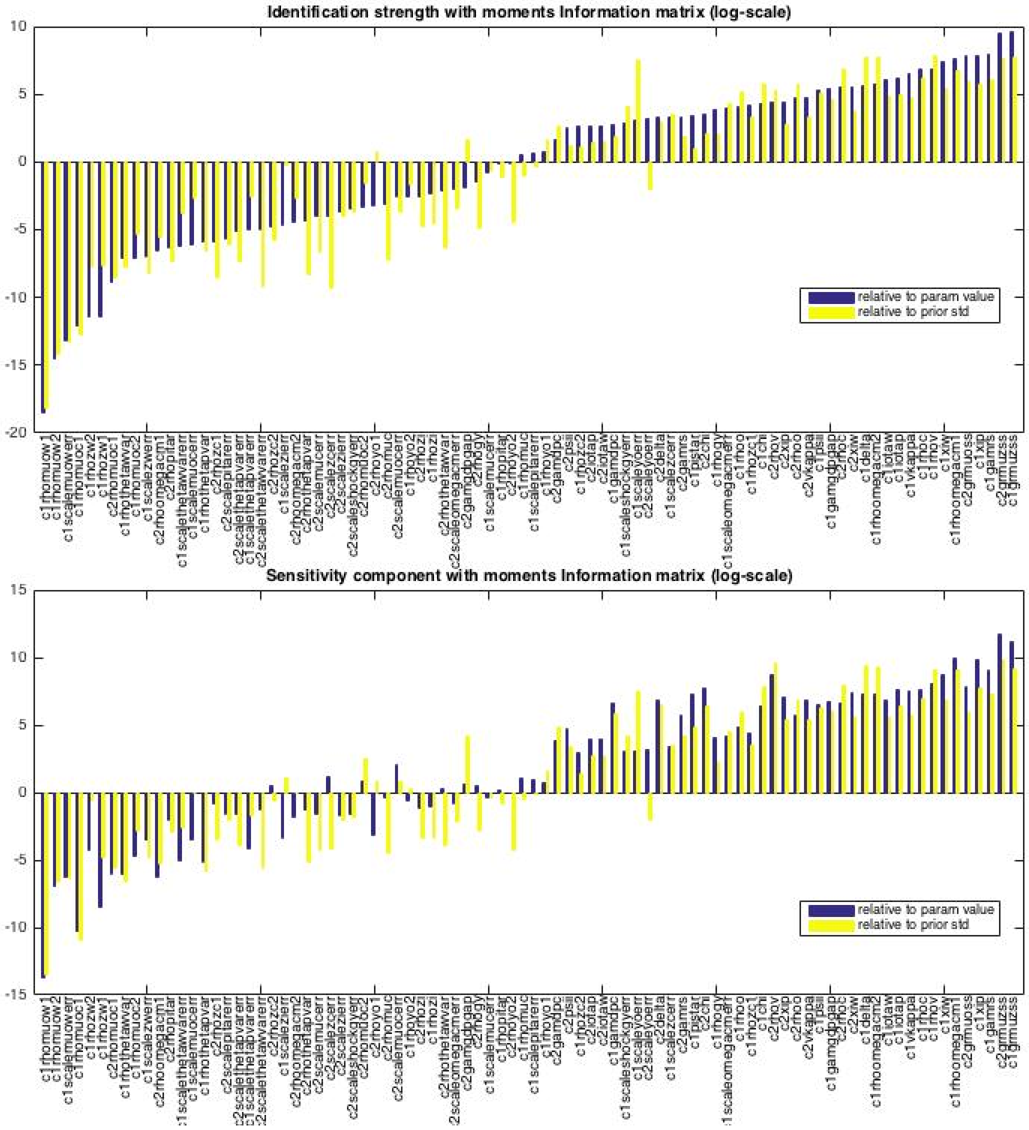

Fig. F.1 Identification strength of the parameters for the Japanese economy normalized by either the parameter at the prior mean (blue bars) or by the standard deviation at the prior mean (red bars).

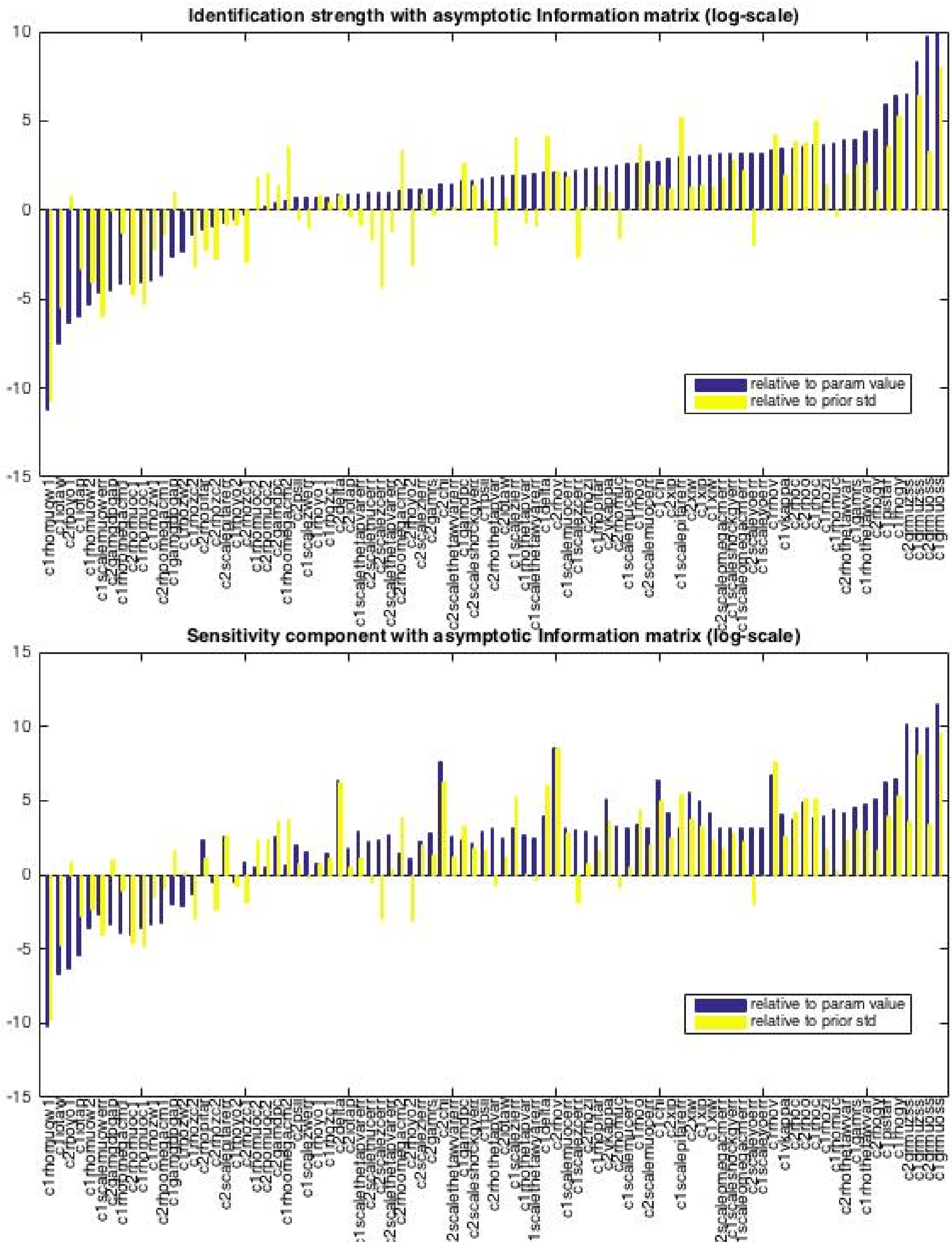

Fig. F.2 Identification strength of the parameters for the U.S. economy normalized by either the parameter at the prior mean (blue bars) or by the standard deviation at the prior mean (red bars).

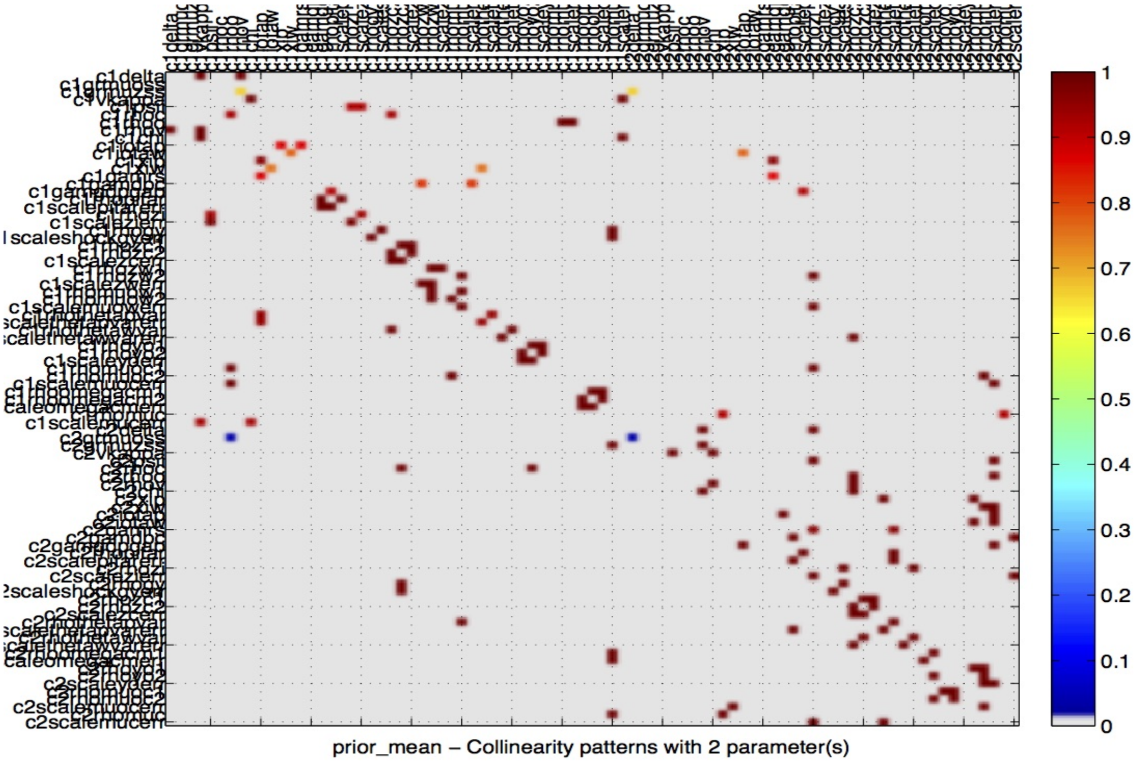

Fig. F.3 Collinearity patterns with 2 parameter(s) from the U.S. Model.The plot shows which linear combination of parameters shown in the columns best replicates replaces the effect of the parameter depicted in the row on the moments of the observables. Higher values imply the relative redundancy and thus weak or un-identifiability of the parameter under consideration. The aim is finding the column (and thus parameter) combination with the highest R2. The resulting collinearity pattern between the parameter in the row and the set of parameters in the columns is then shown in the figure. The darker red the squares are, the more critical is the collinearity between parameters. For example, the first row signifies that there is a strong correlation between the effect of the depreciation rate of the capital on the model moments and the effect of capital substition elasticity (Pfeifer, 2014).

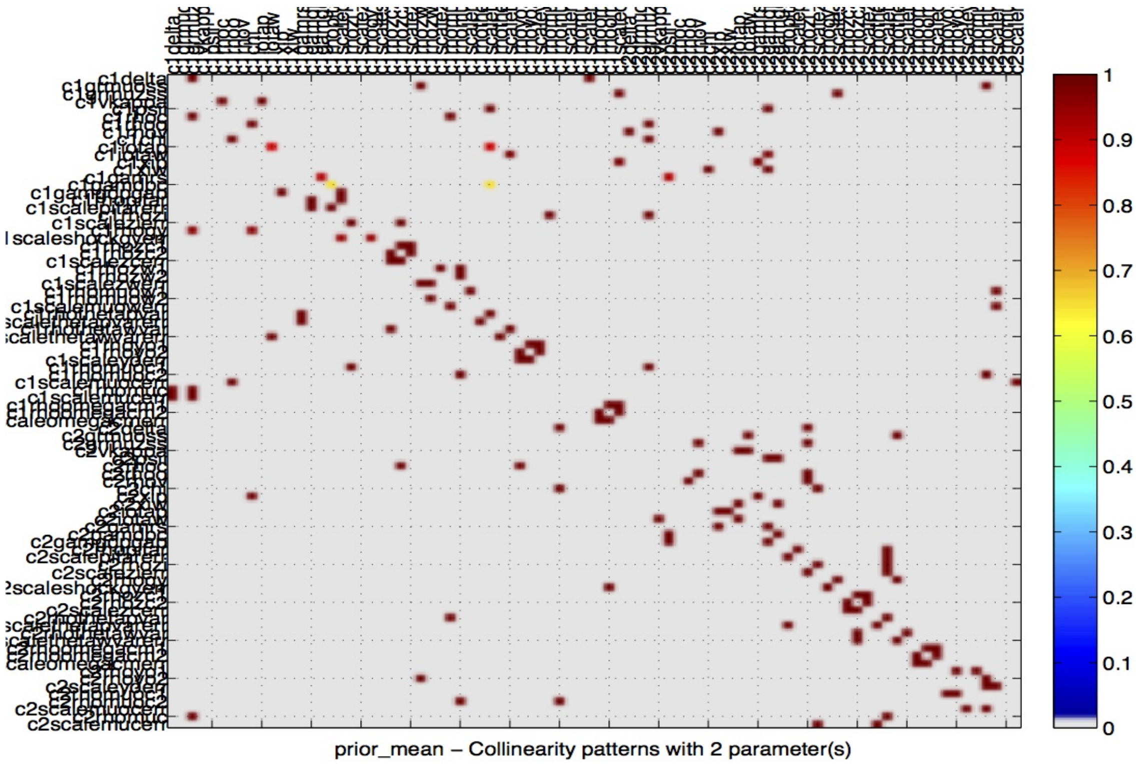

Fig. F.4 Collinearity patterns with 2 parameter(s) from the Japan Model.The plot shows which linear combination of parameters shown in the columns best replicates replaces the effect of the parameter depicted in the row on the moments of the observables. Higher values imply the relative redundancy and thus weak or un-identifiability of the parameter under consideration. The aim is finding the column (and thus parameter) combination with the highest R2. The resulting collinearity pattern between the parameter in the row and the set of parameters in the columns is then shown in the figure. The darker red the squares are, the more critical is the collinearity between parameters. For example, the first row signifies that there is a strong correlation between the effect of the depreciation rate of the capital on the model moments and the effect of capital substitution elasticity (Pfeifer, 2014).

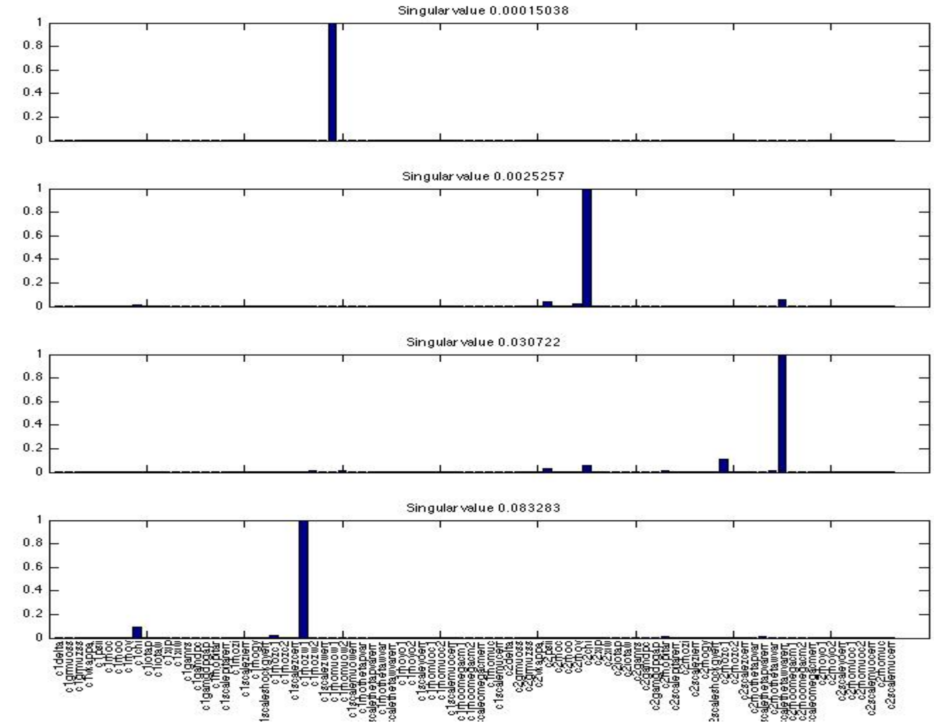

Fig. F.5 `Prior_mean`. Identification patterns (Information matrix): SMALLEST SV from the U.S. Model. Identification pattern-plot generated by the identification-command. It is stored in the identification subfolder. Following Andrle (2010), the parameter groups with the strongest and weakest identification can be identified from the singular value decomposition (Singular Value Decomposition (SVD)) of the Fischer information matrix. This graph shows the smallest singular values (Singular Value (SV)) and the associated eigenvectors of parameters. The parameter combinations associated with the smallest singular values are closest to being perfectly collinear and thus redundant (Pfeifer, 2014).

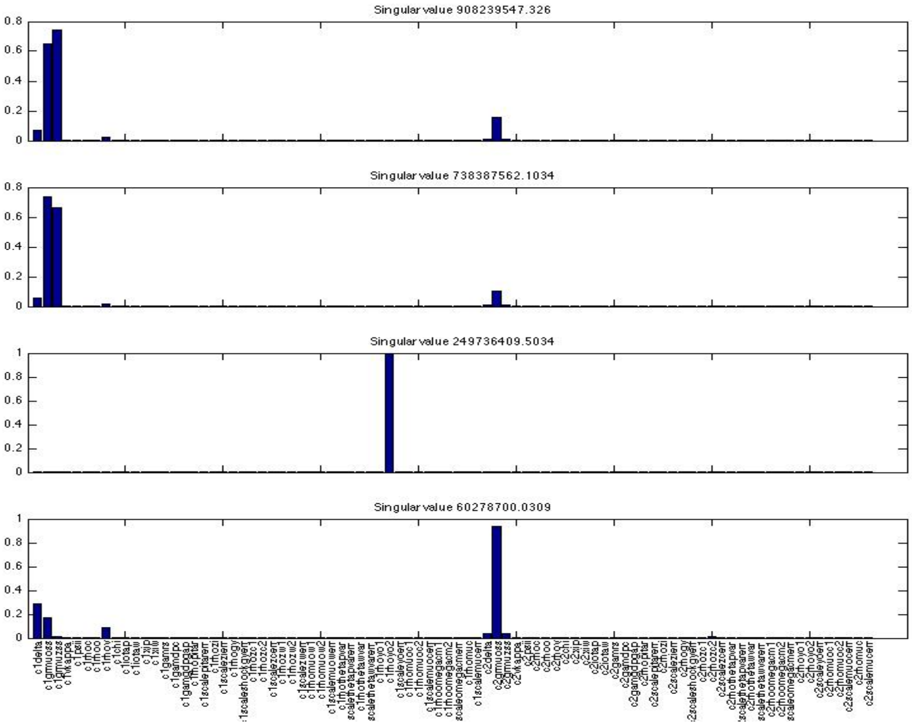

Fig. F.6 `Prior_mean`. Identification patterns (Information matrix): HIGHEST SV from the U.S. Model. Identification pattern-plot generated by the identification-command. It is stored in the identification subfolder. This graph shows the largest singular values and the associated eigenvectors of parameters. It has the same interpretation as the graph for the smallest singular values, Figure 29, except for now depicting the parameters being most uncorrelated and thus best identified (Pfeifer, 2014).

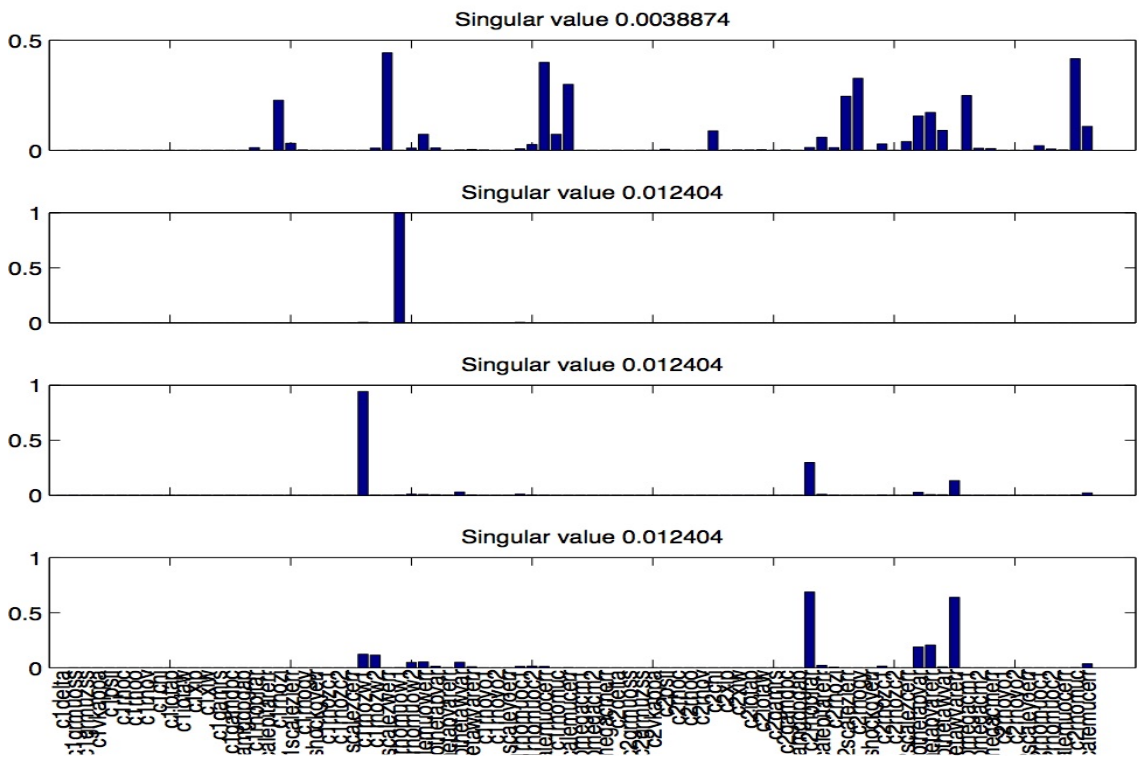

Fig. F.7 `Prior_mean`. Identification patterns (Information matrix): SMALLEST SV from the Japan Model.Identification pattern-plot generated by the identification-command. It is stored in the identification subfolder. Following Andrle (2010), the parameter groups with the strongest and weakest identification can be identified from the singular value decomposition (Singular Value Decomposition (SVD)) of the Fischer information matrix. This graph shows the smallest singular values (Singular Value (SV)) and the associated eigenvectors of parameters. The parameter combinations associated with the smallest singular values are closest to being perfectly collinear and thus redundant (Pfeifer, 2014).

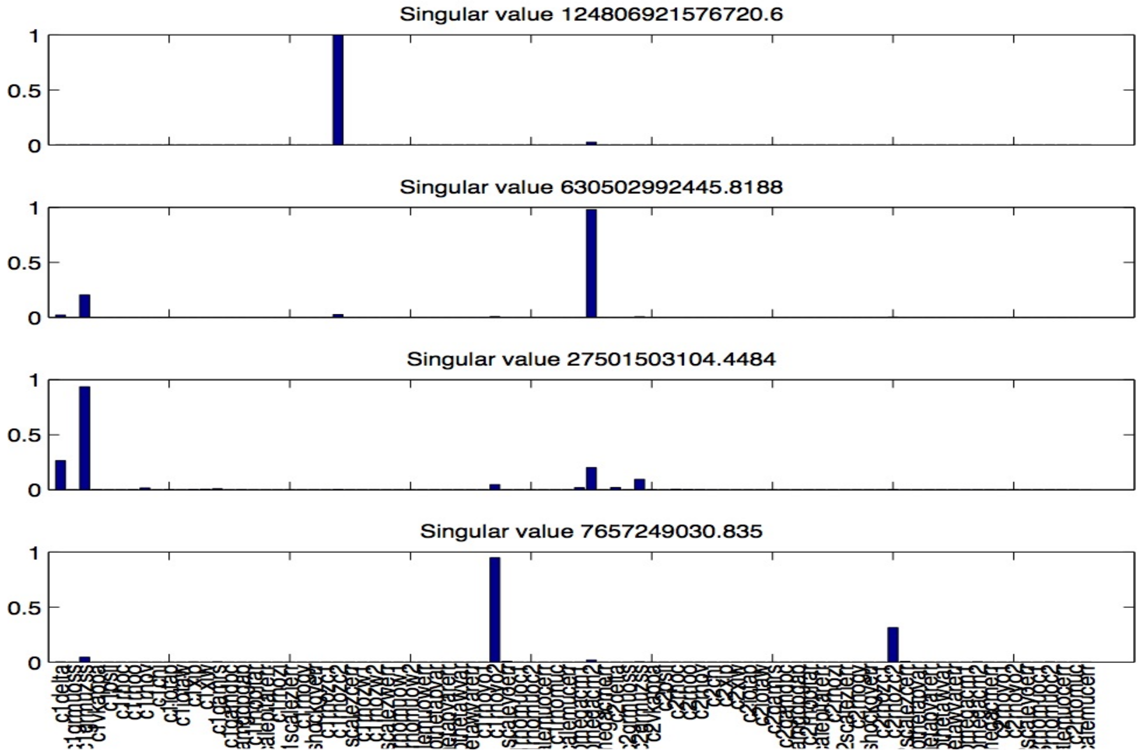

Fig. F.8 `Prior_mean`. Identification patterns (Information matrix): HIGHEST SV from the Japan Model. Identification pattern-plot generated by the identification-command. It is stored in the identification subfolder. This graph shows the largest singular values and the associated eigenvectors of parameters. It has the same interpretation as the graph for the smallest singular values, Figure 29, except for now depicting the parameters being most uncorrelated and thus best identified (Pfeifer, 2014).

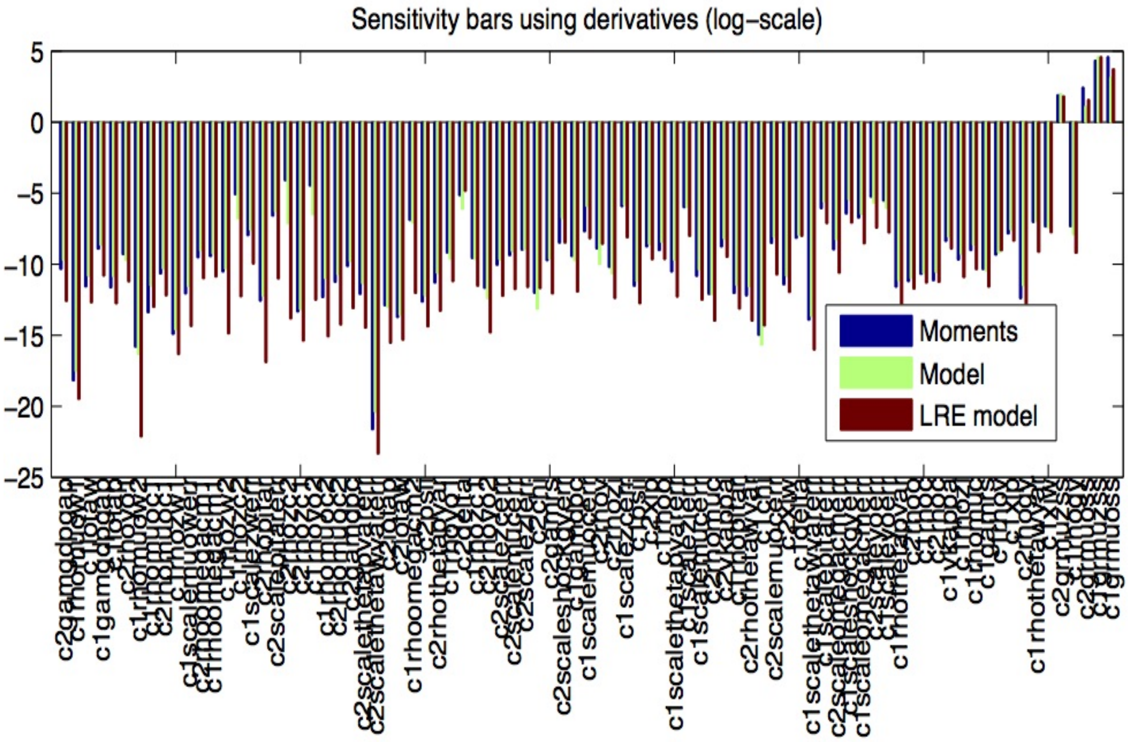

Fig. F.9 MC sensitivity from the U.S. Model.The bars shown in the figure depict the norm of the columns of three different standardized Jacobian matrices for the respective parameter shown on the xaxis. Jacobian matrices refer to: The moments matrix blue bars, depict how well a parameter can be identified due the strength of its impact on the observed moments. The model solution matrices, green bars depict how well a parameter could in principle be identified if all state variables were observed, and the Linear Rational Expectations (LRE) model , red bars depict trivial cases of nonidentifiability due to e.g. some parameters always showing up as a product only in the model equations. If the moment matrix (blue bars) indicates nonidentifiability and the model solution matrix (green bars) indicates identifiability, it means that your observables in the varobscommand are not sufficient (Pfeifer, 2014).

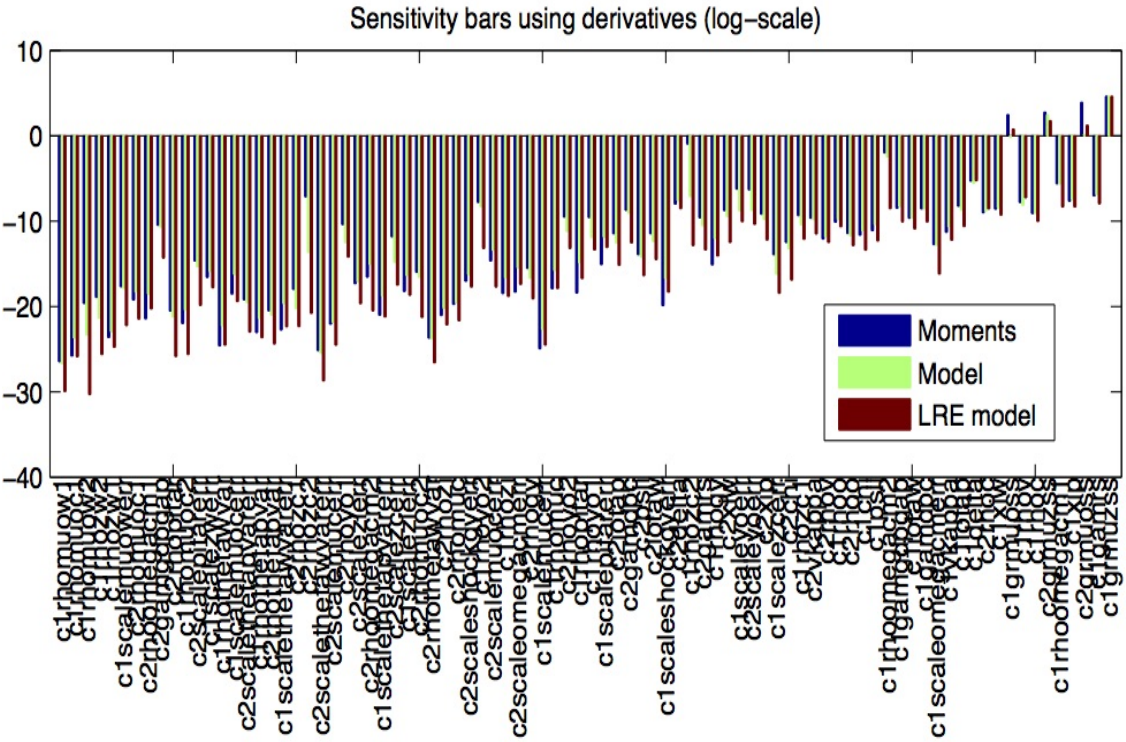

Fig. F.10]

MC sensitivity from the Japan Model.The bars shown in the figure depict the norm of the columns of three different standardized Jacobian matrices for the respective parameter shown on the xaxis. Jacobian matrices refer to: The moments matrix blue bars, depict how well a parameter can be identified due the strength of its impact on the observed moments. The model solution matrices, green bars depict how well a parameter could in principle be identified if all state variables were observed, and the Linear Rational Expectations (LRE) model , red bars depict trivial cases of nonidentifiability due to e.g. some parameters always showing up as a product only in the model equations. If the moment matrix (blue bars) indicates nonidentifiability and the model solution matrix (green bars) indicates identifiability, it means that your observables in the varobscommand are not sufficient (Pfeifer, 2014).

Appendix G

Groups of the 22 Exogenous Shocks

Table G.1 Shock groups from the 22 exogenous shocks. The meaning of alphabetic letters is F. for foreign, H. for Home and I. for International

Group	Shocks			
Supply	*H. Government*	*F. Government*	*Investments*	
Demand	*H. Consumption*	*F. Consumption*	*Wage Markup*	*Imports*
Monetary	*H. Monetary Policy*	*F. Monetary Policy*	*Price Markup*	
World Oil Supply	*W. Oil Supply*			
Home Oil Supply	*H. Oil Supply*			
World Technology	*F. Technology*	*I. technology*		
Home Technology	*H. Technology*			
World oil efficiency	*F. oil efficiency*	*I. oil efficiency*		
Home oil efficiency	*H. oil efficiency*			

Appendix H

Shocks Decomposition Plots Small Identity Matrix

We must remark that we had tremendous difficulties to find the posterior mode of our estimated parameters due to the high complexity and dimension of our model (244 endogenous variables, 22 exogenous shocks and more than a hundred estimated parameters). Consequently, we initial also worked with a small identity matrix in order to obtain a positive definite Hessian. We replaced the line chol(hh); in the try-catch-statement of `dynare_estimation_1.m` by $hh = 1e-4*eye(size(hh))$. A best alternative procedure, although much more complicate, is described by Gill and King (2004). The plots of the present Appendix were computed following the referred calculation method.

H.1 Economic reaction to the post-WW II oil shocks

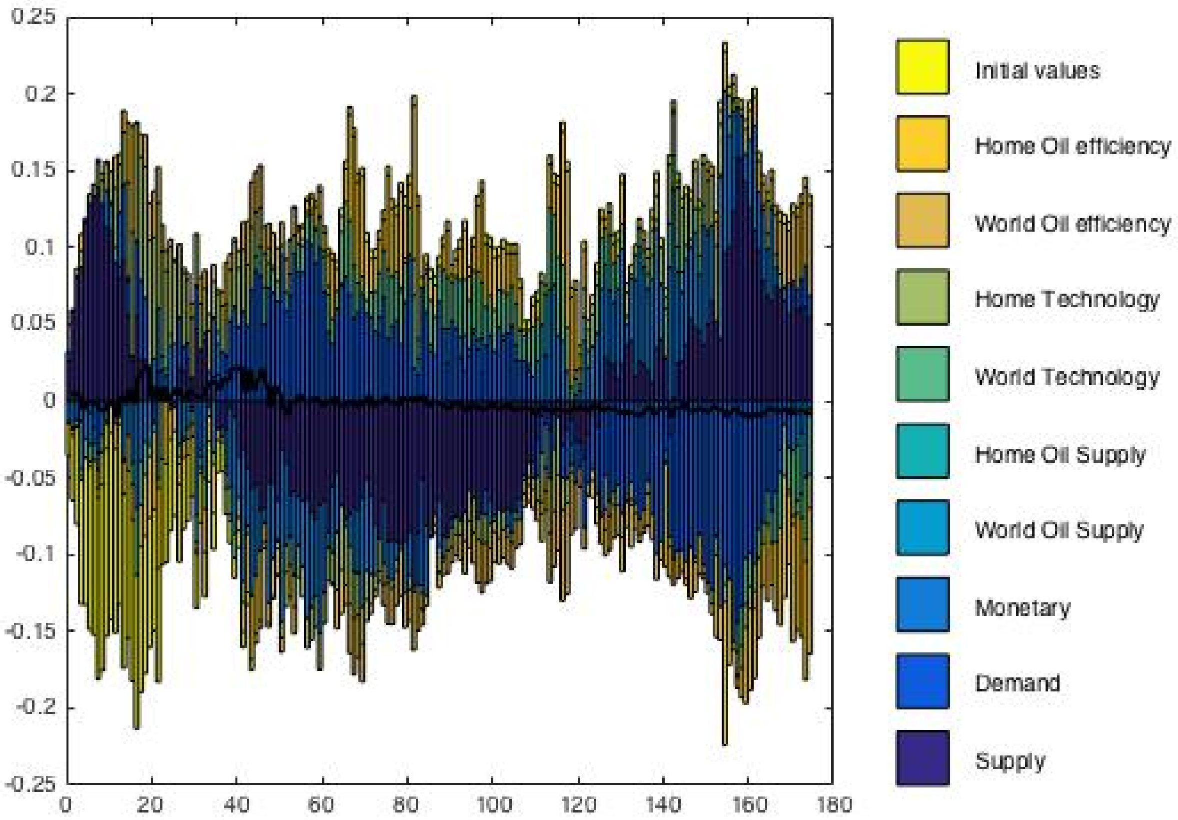

Fig. H.1 Shock decomposition plot of domestic inflation in the U.S.. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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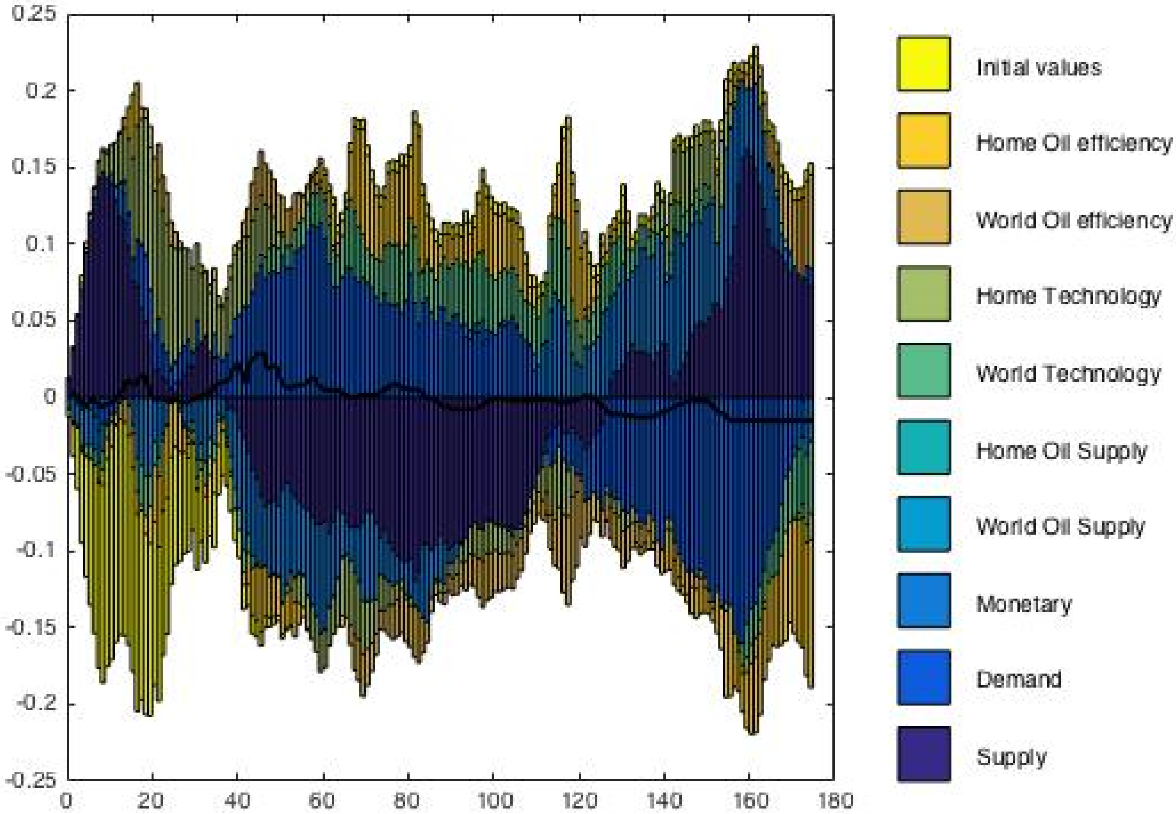

Fig. H.2 Shock decomposition plot of interest rates in the U.S.. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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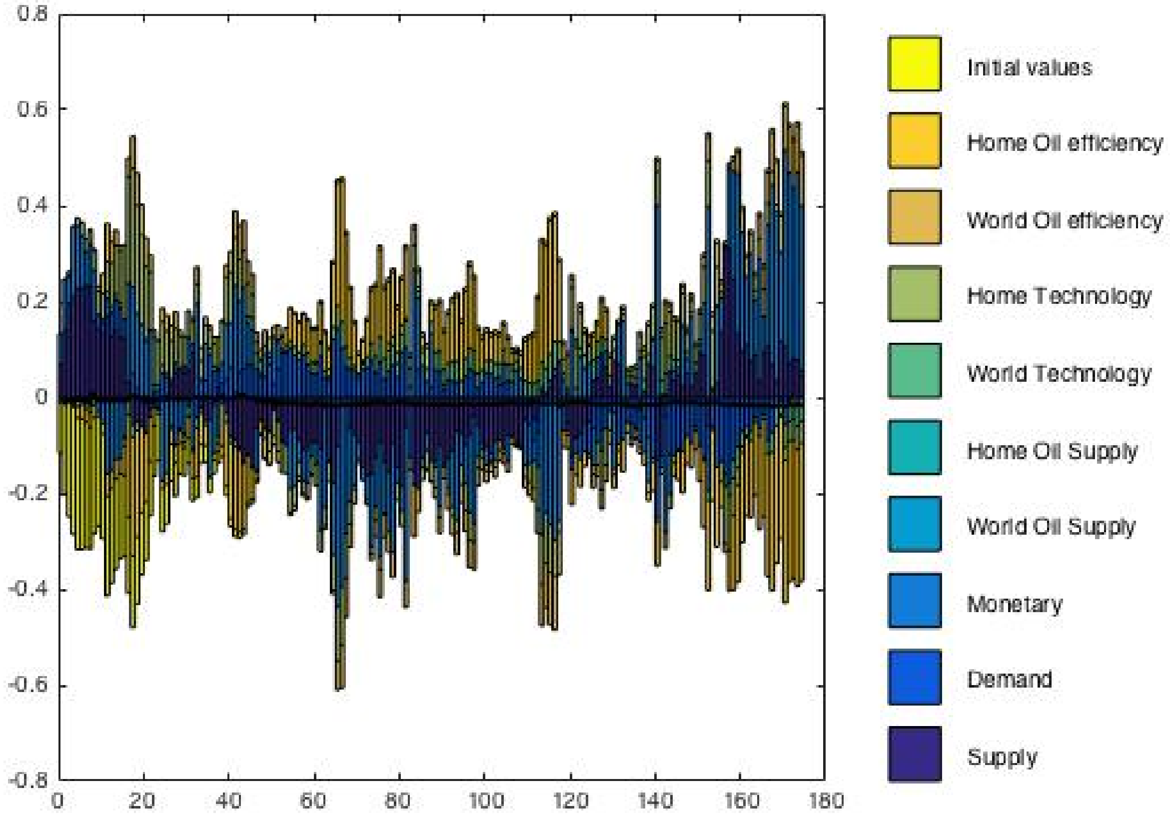

Fig. H.3 Shock decomposition plot of wages inflation in the U.S.. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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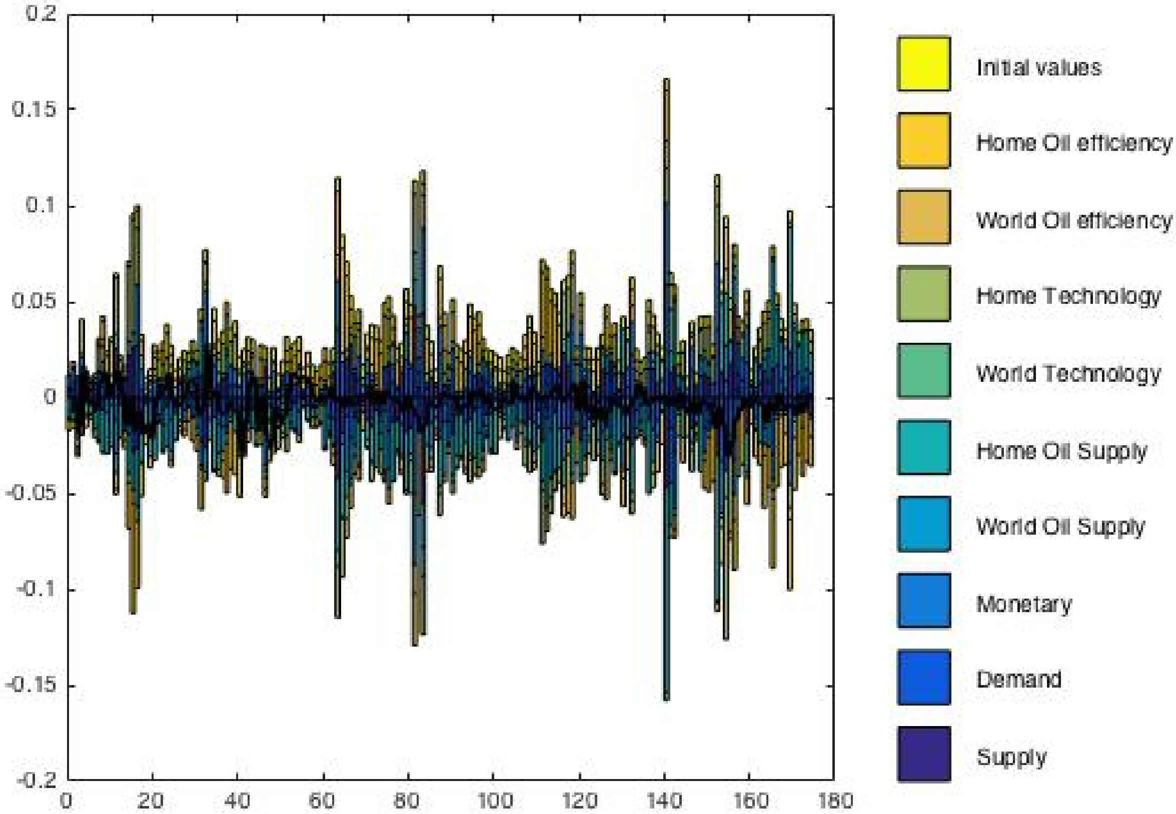

Fig. H.4 Shock decomposition plot of GDP growth in the U.S.. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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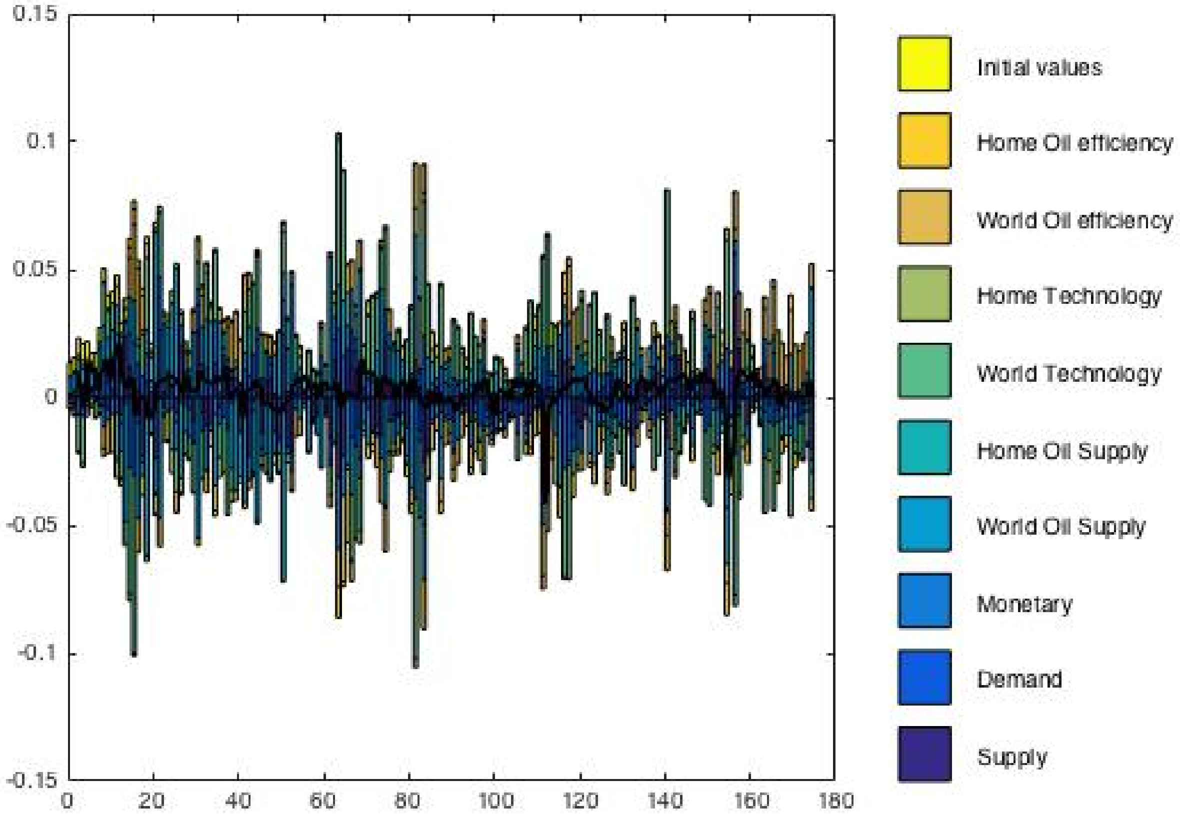

Fig. H.5 Shock decomposition plot of GDP growth in foreign bloc. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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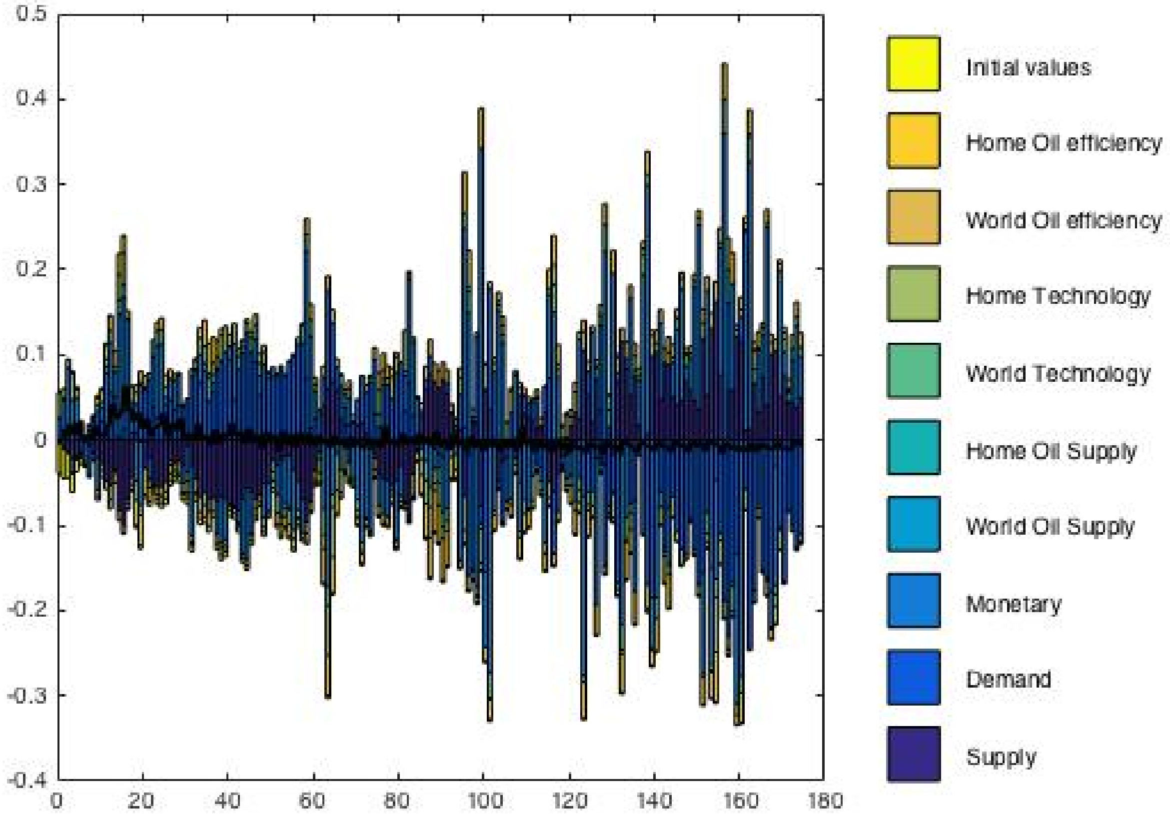

Fig. H.6 Shock decomposition plot of core inflation in Japan. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the to the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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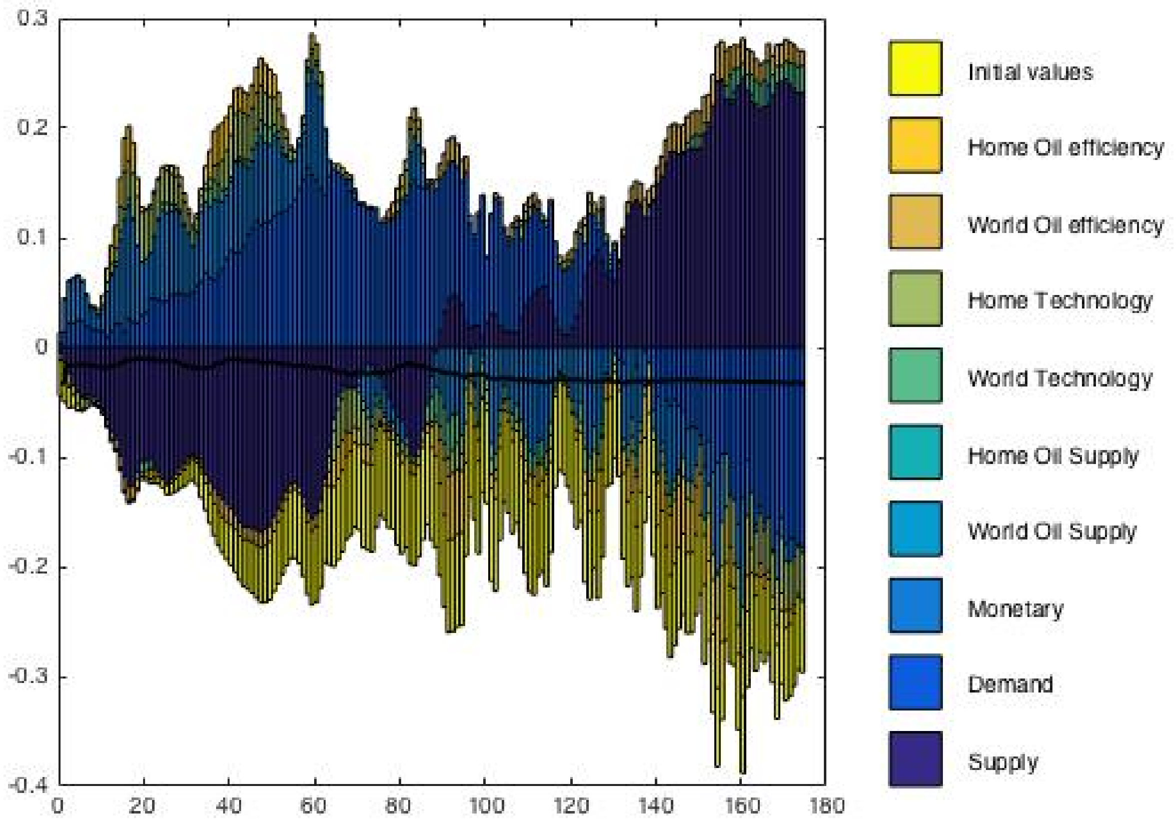

Fig. H.7 Shock decomposition plot of interest rates in Japan. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the to the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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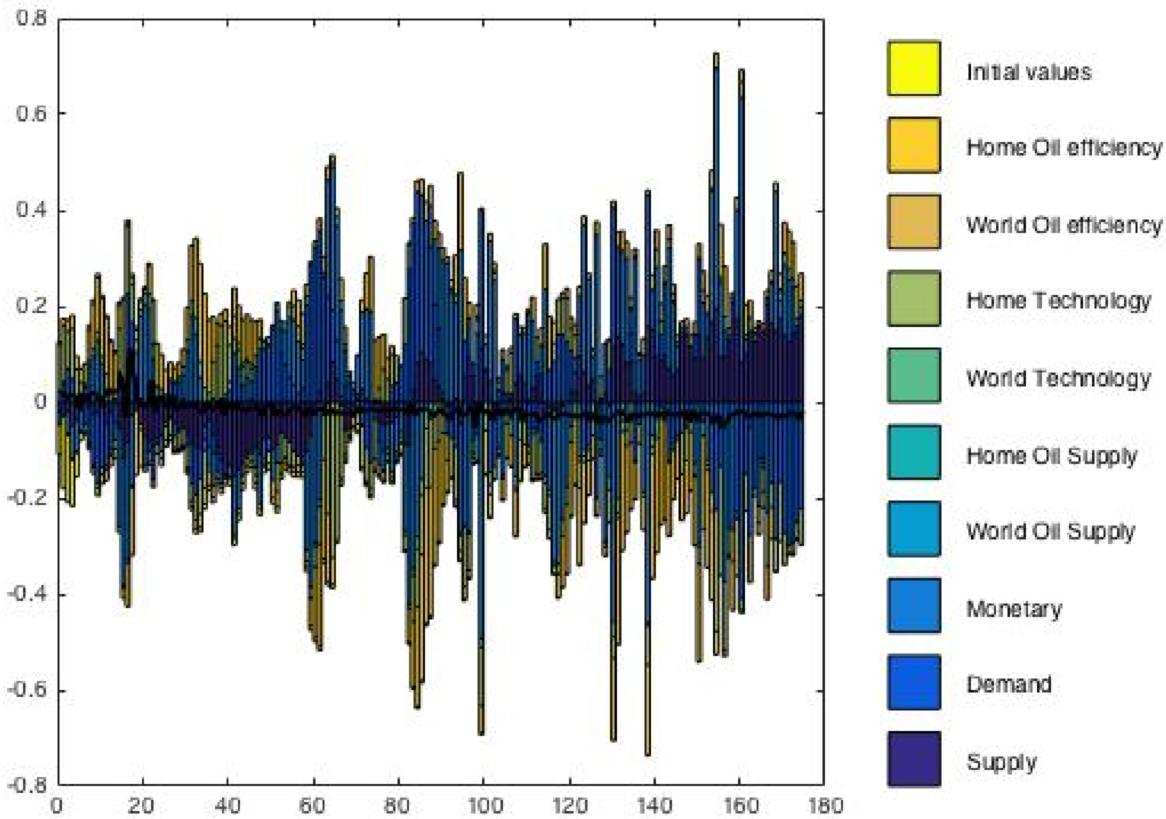

Fig. H.8 Shock decomposition plot of wages inflation in Japan. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the to the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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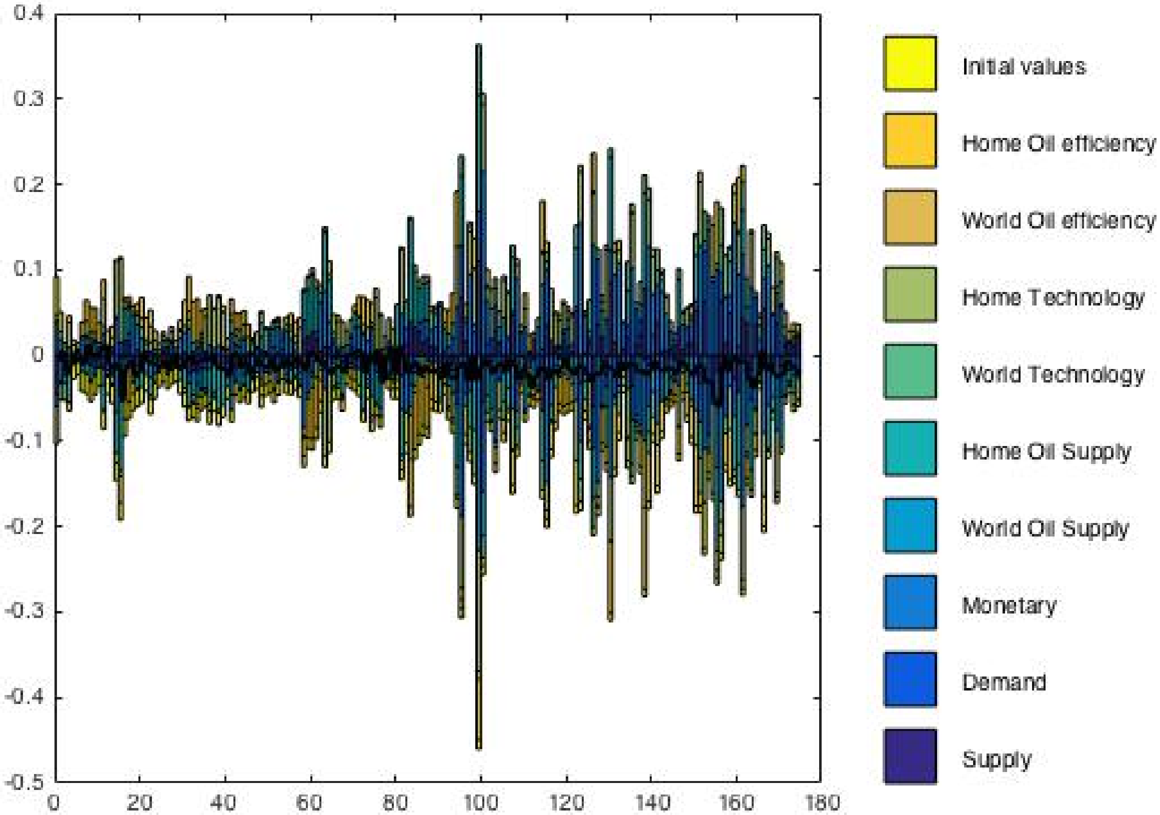

Fig. H.9 Shock decomposition plot of GDP growth in Japan. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the to the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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H.2 Exergy Efficiency Analysis

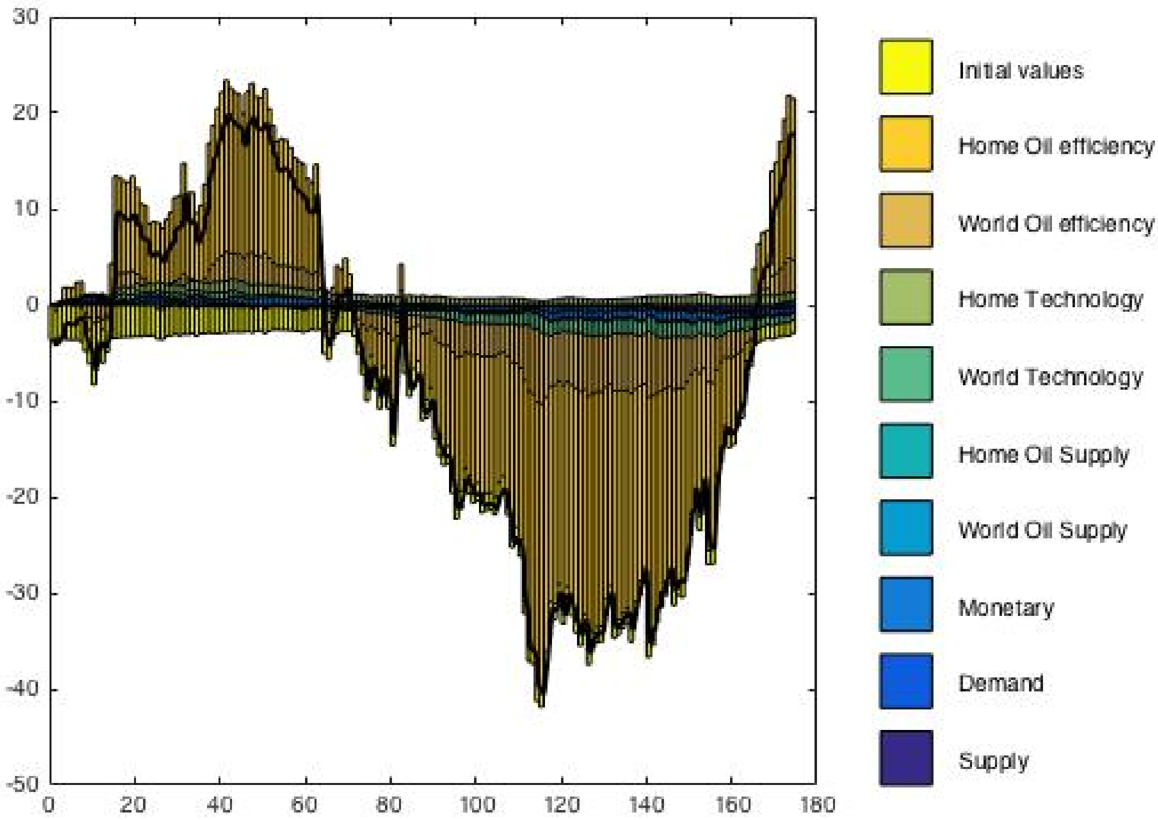

Fig. H.10 Shock decomposition plot of the U.S. oil consumption. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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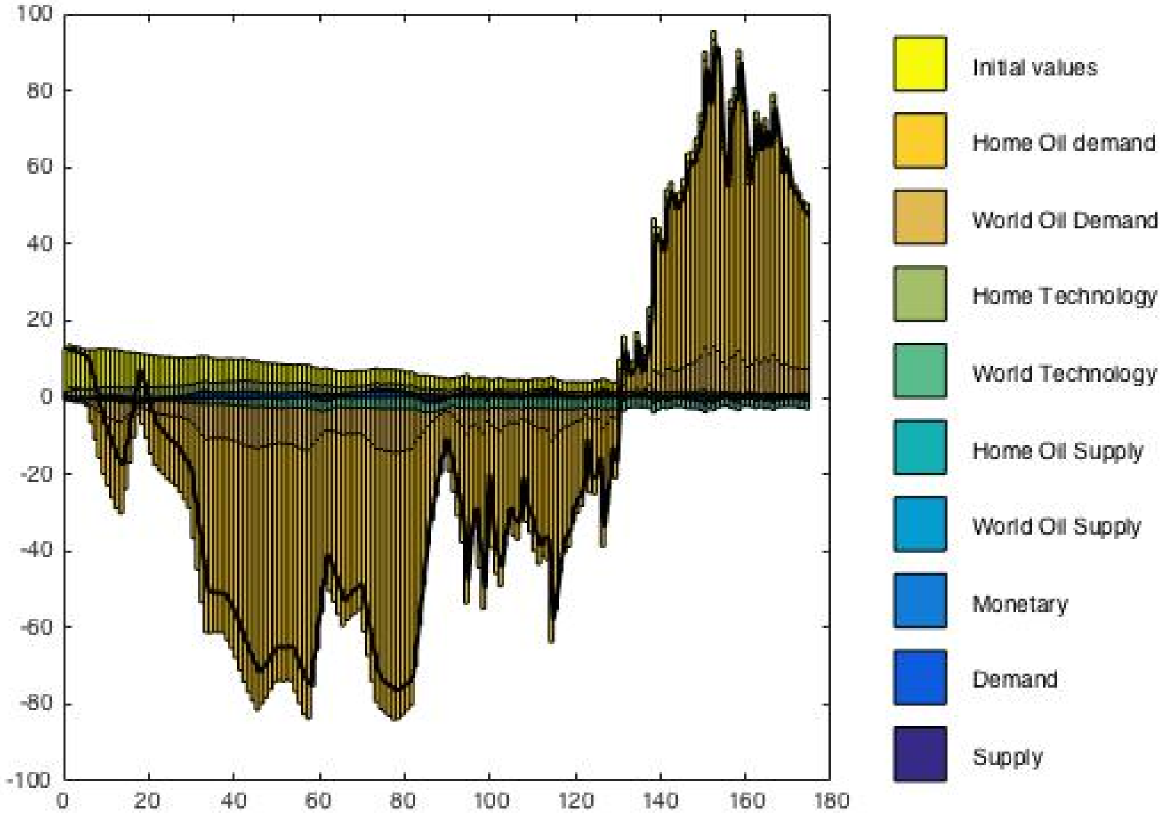

Fig. H.11 Shock decomposition plot of the Japan oil consumption. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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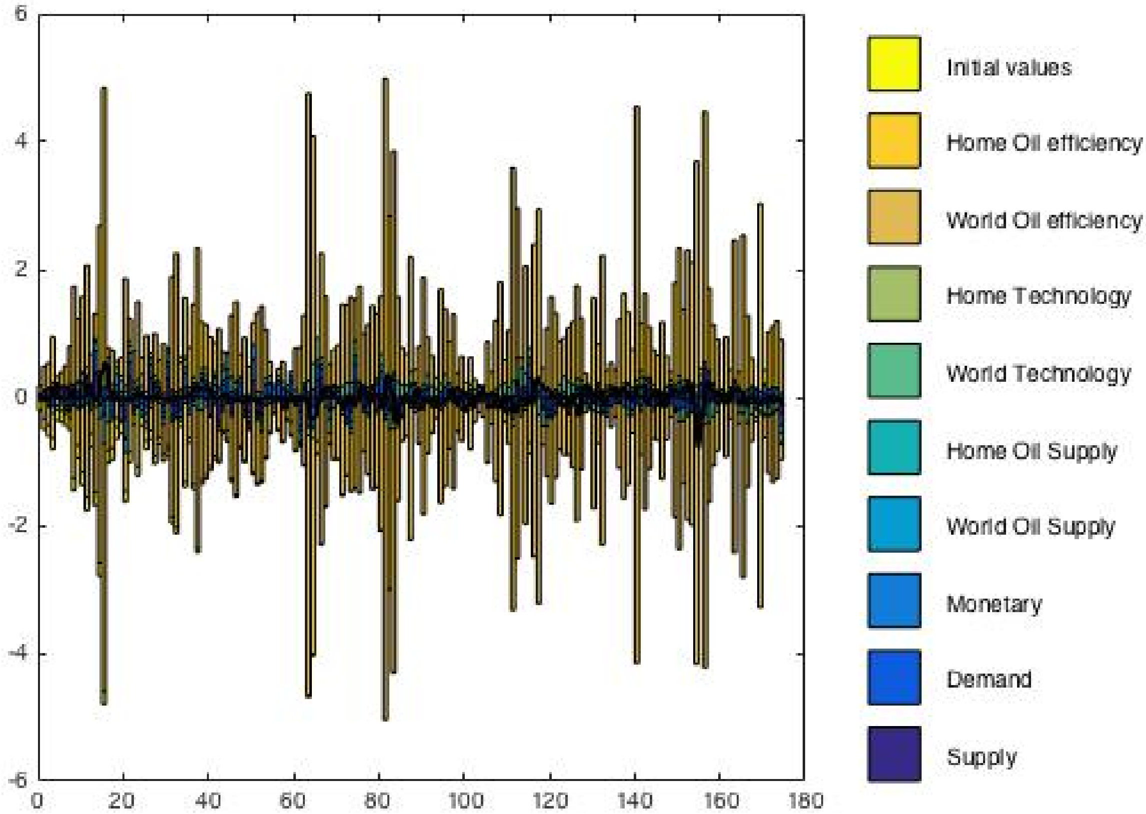

Fig. H.12 Shock decomposition plot of the U.S. oil price. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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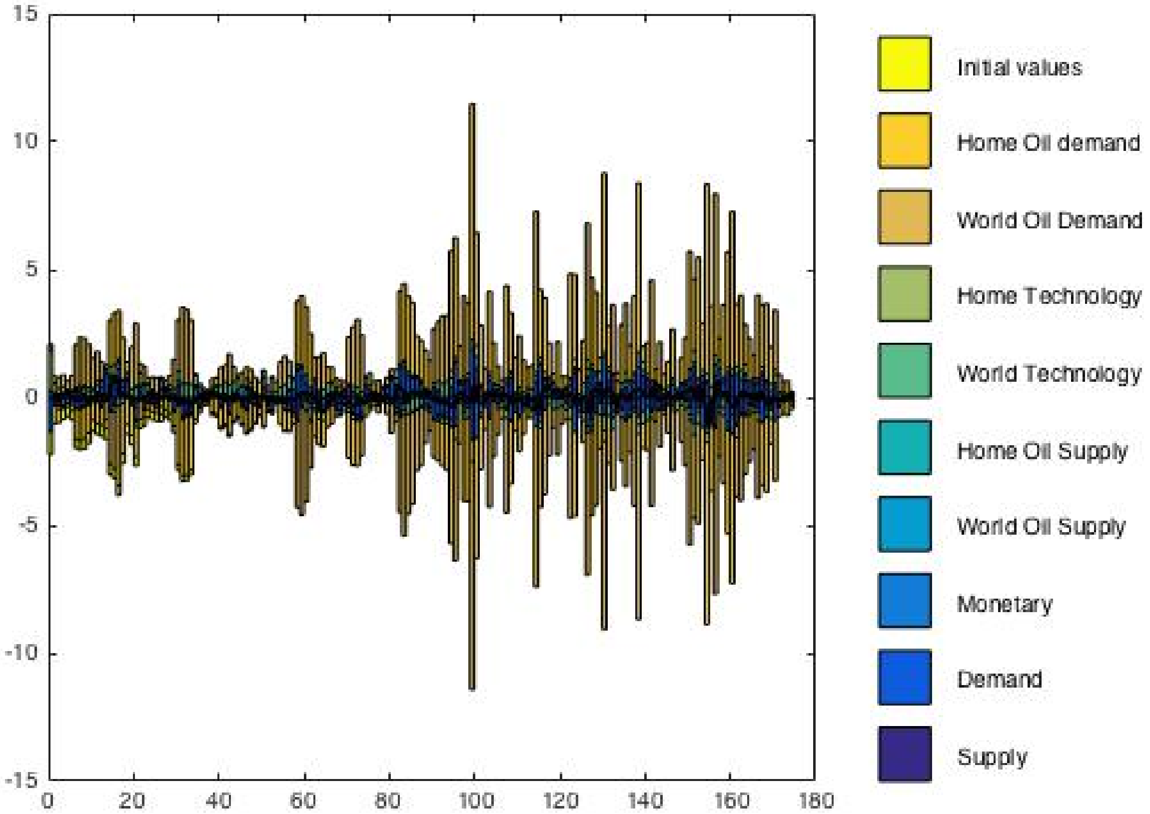

Fig. H.13 Shock decomposition plot of Japan oil price. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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Appendix I

Shock Decomposition Plots

I.1 Economic reaction to the post-WW II oil shocks

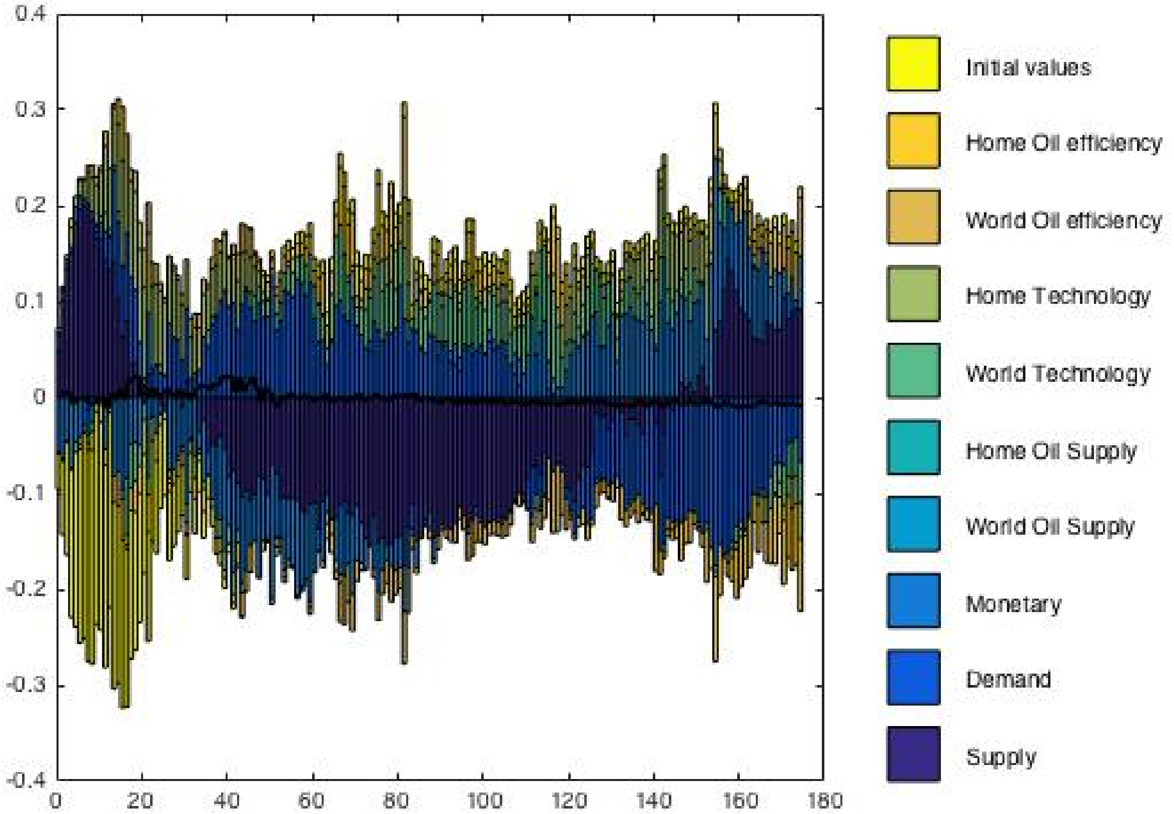

Fig. I.1 Shock decomposition plot of domestic inflation in the U.S.. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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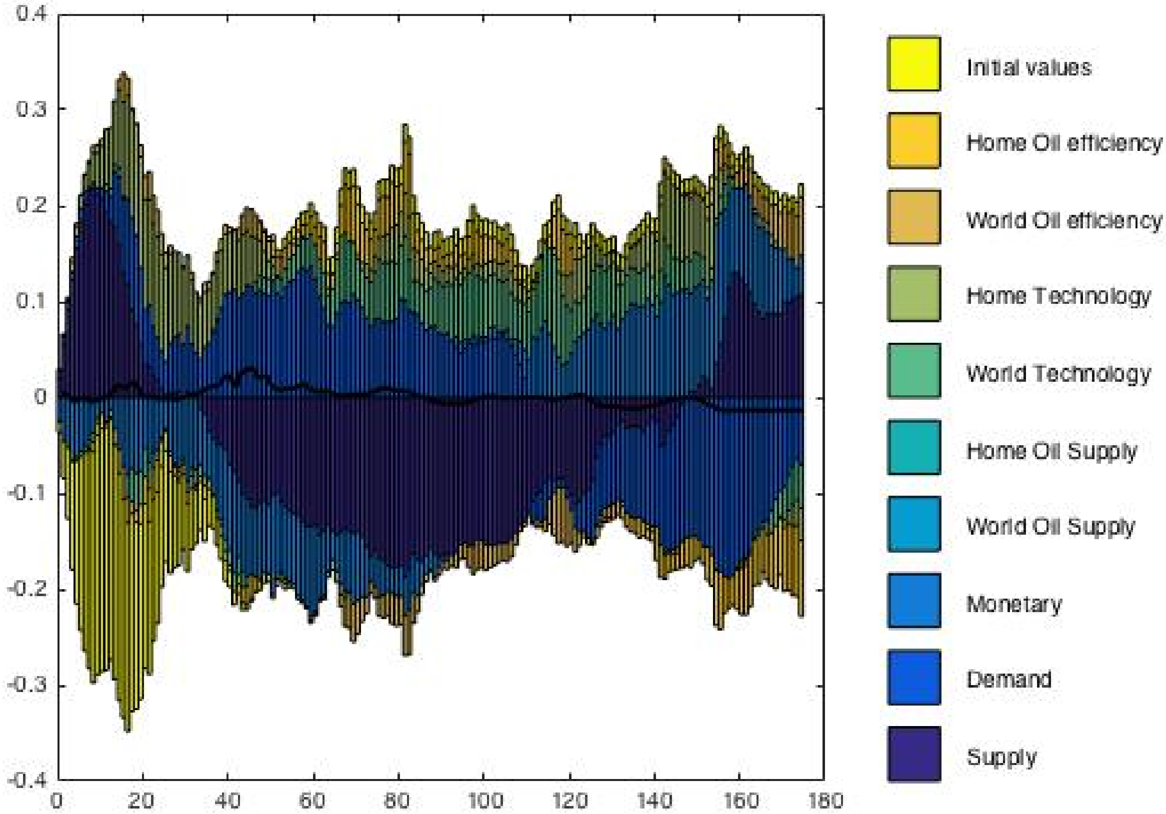

Fig. I.2 Shock decomposition plot of interest rates in the U.S.. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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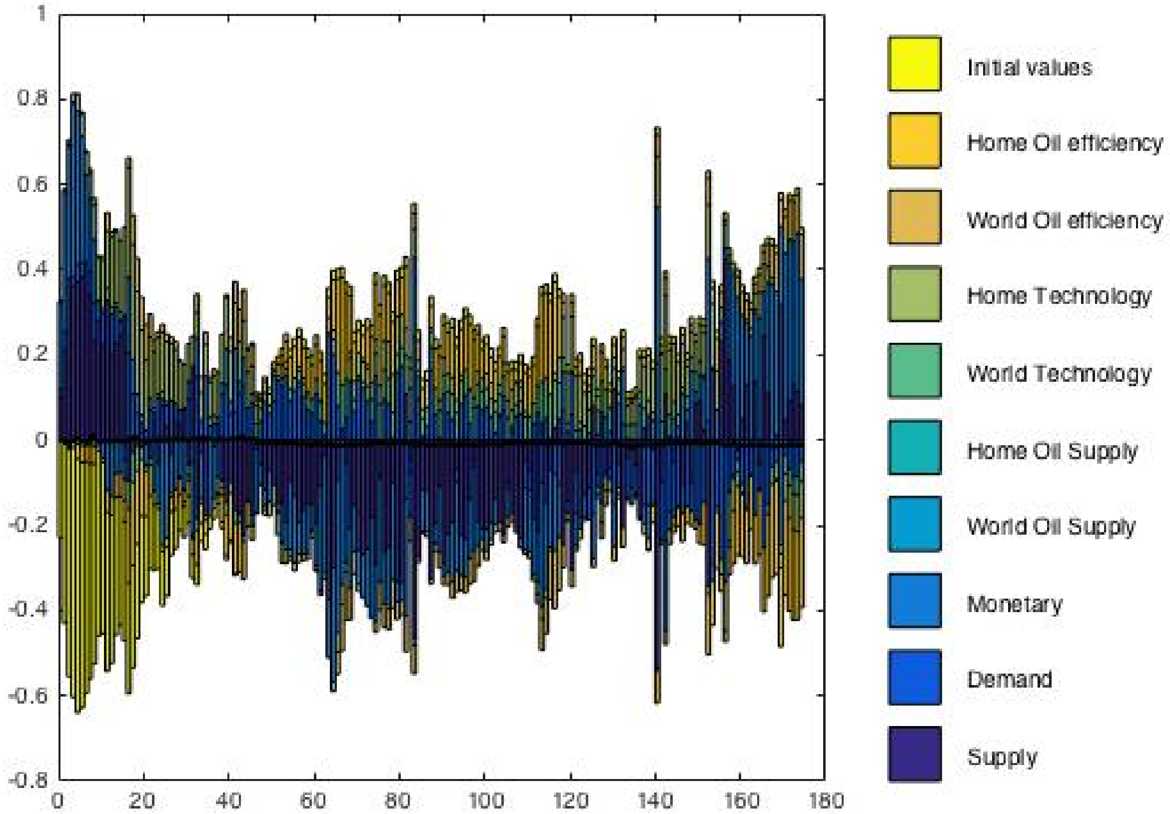

Fig. I.3 Shock decomposition plot of wages inflation in the U.S.. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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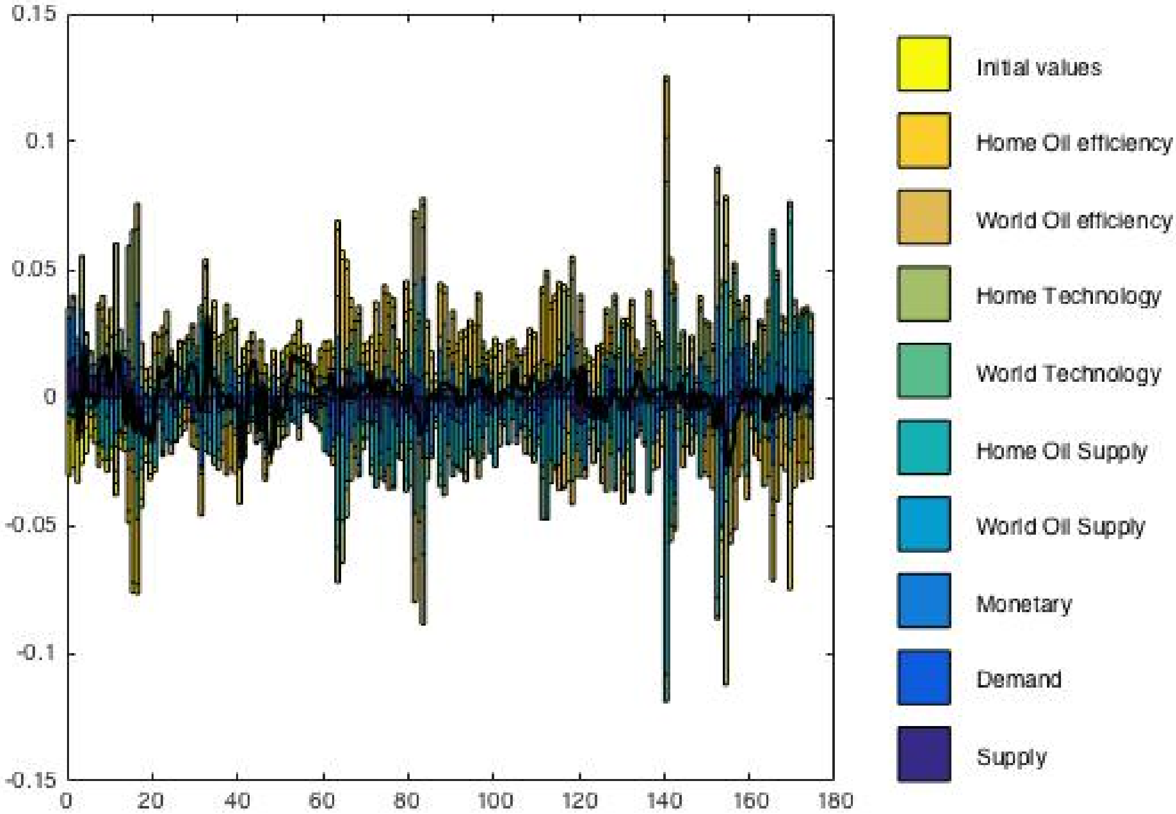

Fig. I.4 Shock decomposition plot of GDP growth in the U.S.. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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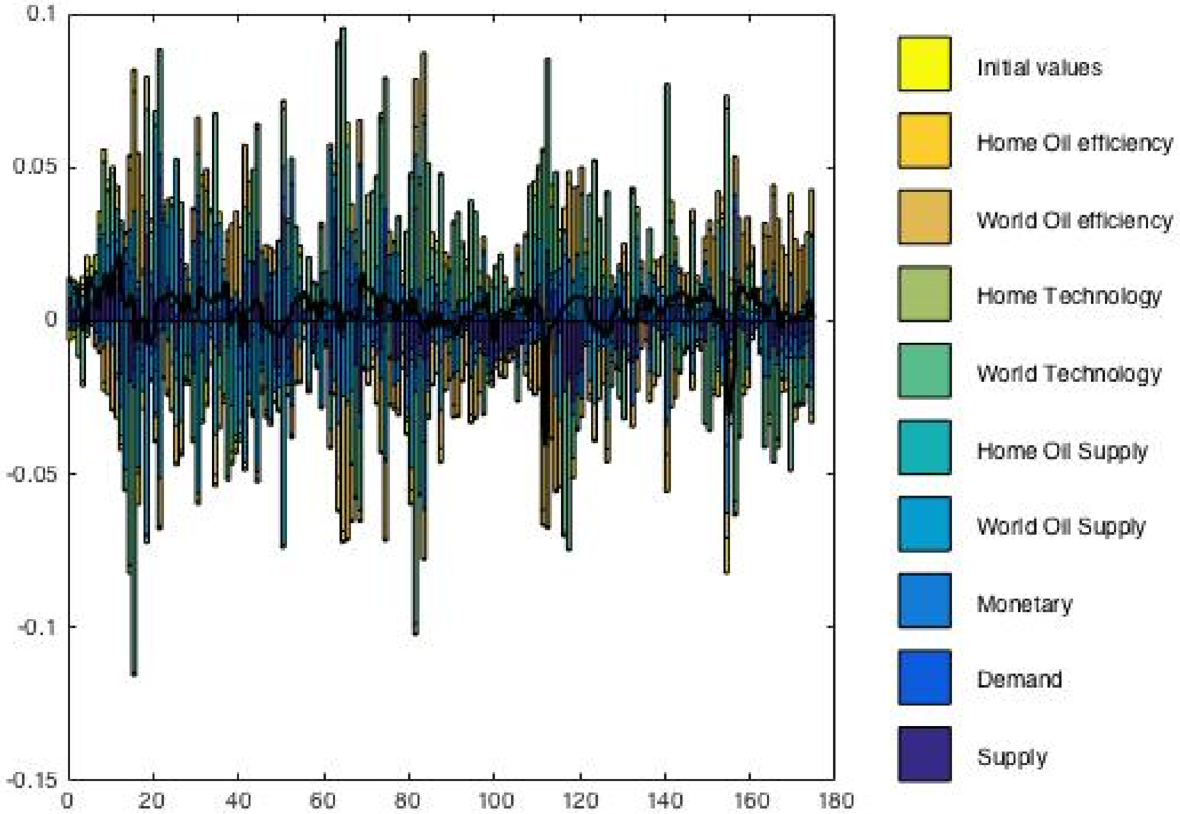

Fig. I.5 Shock decomposition plot of GDP growth in foreign bloc. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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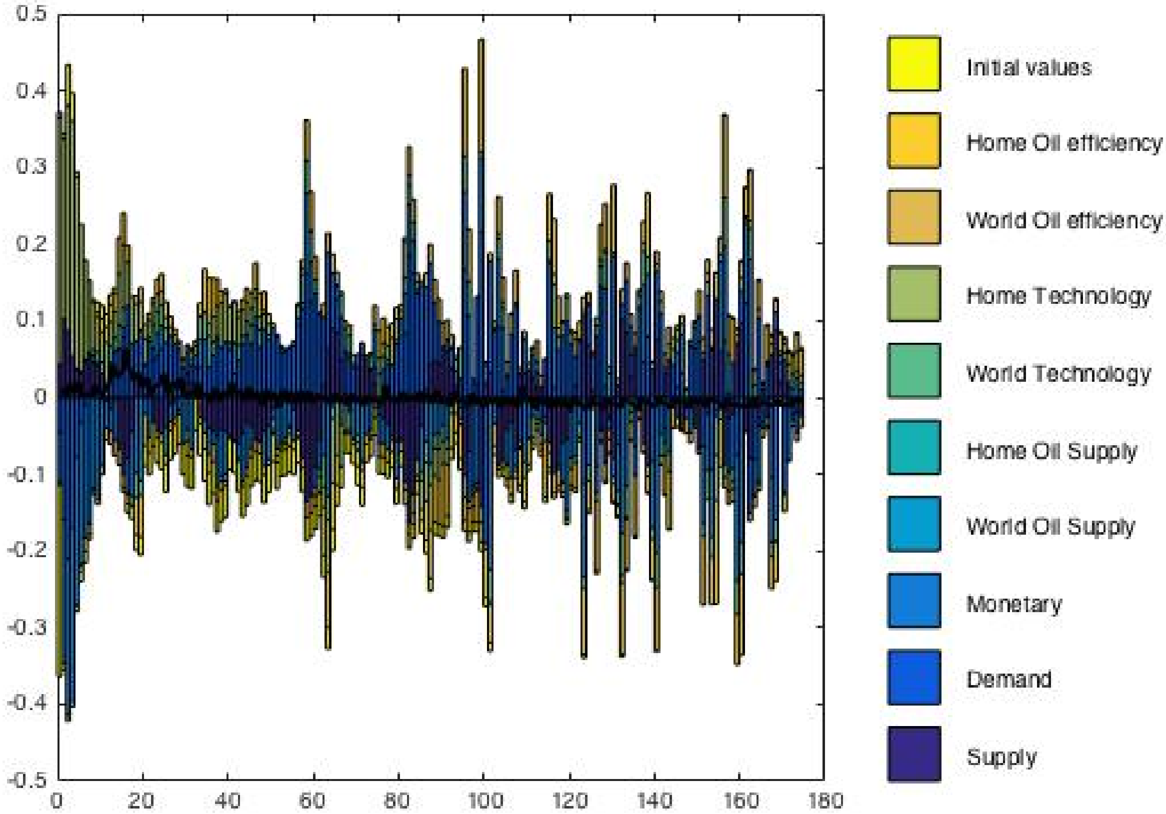

Fig. I.6 Shock decomposition plot of core inflation in Japan. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the to the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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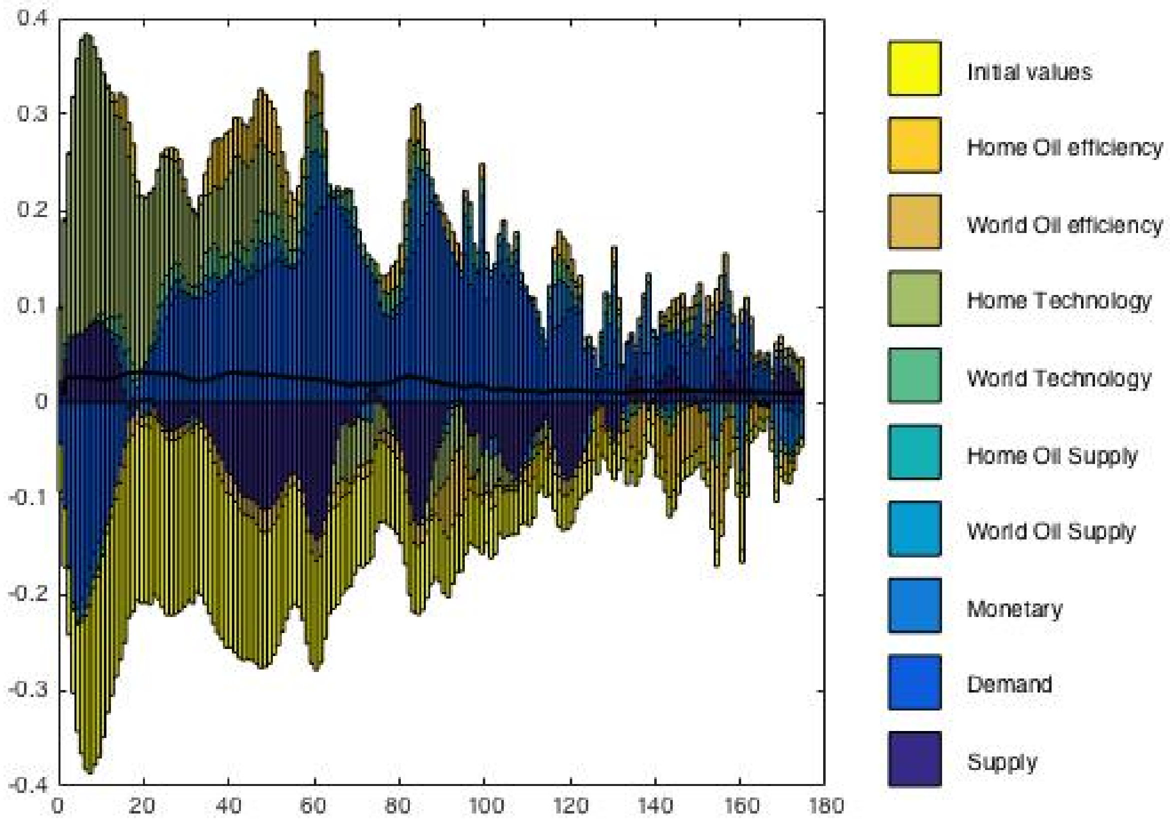

Fig. I.7 Shock decomposition plot of interest rates in Japan. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the to the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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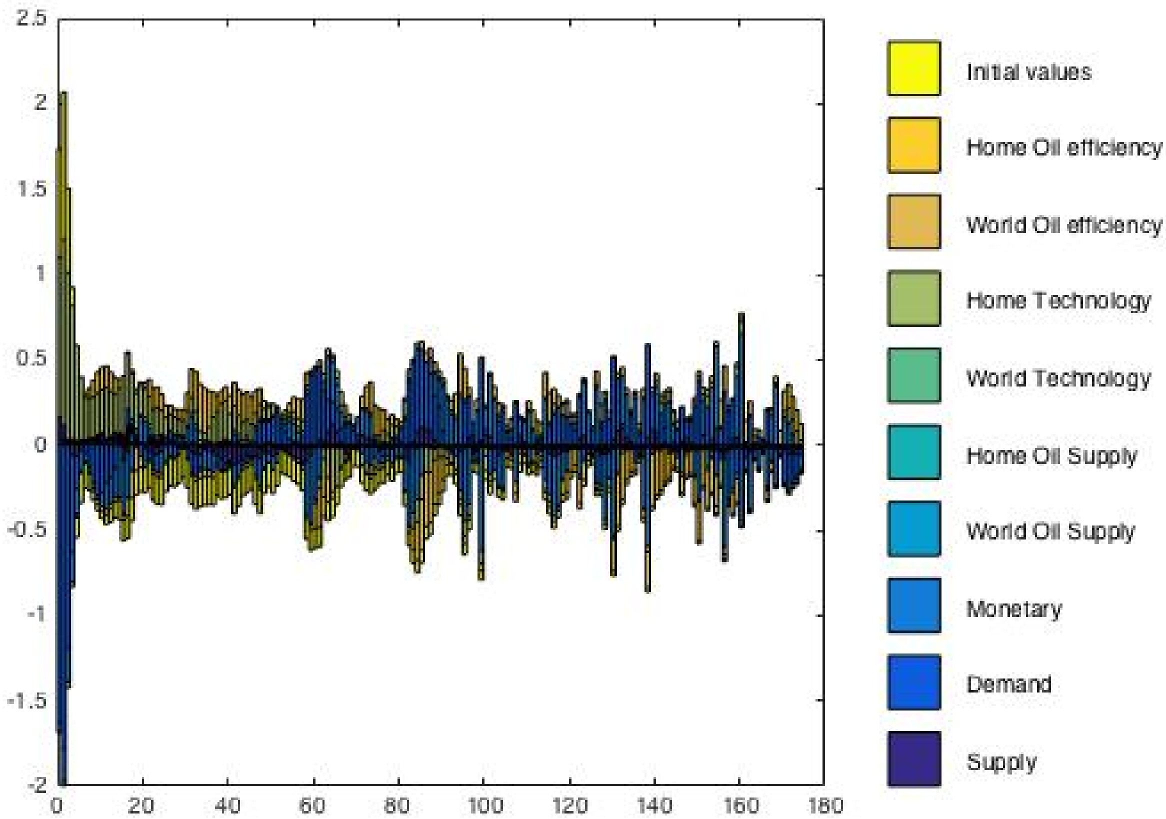

Fig. I.8 Shock decomposition plot of wages inflation in Japan. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the to the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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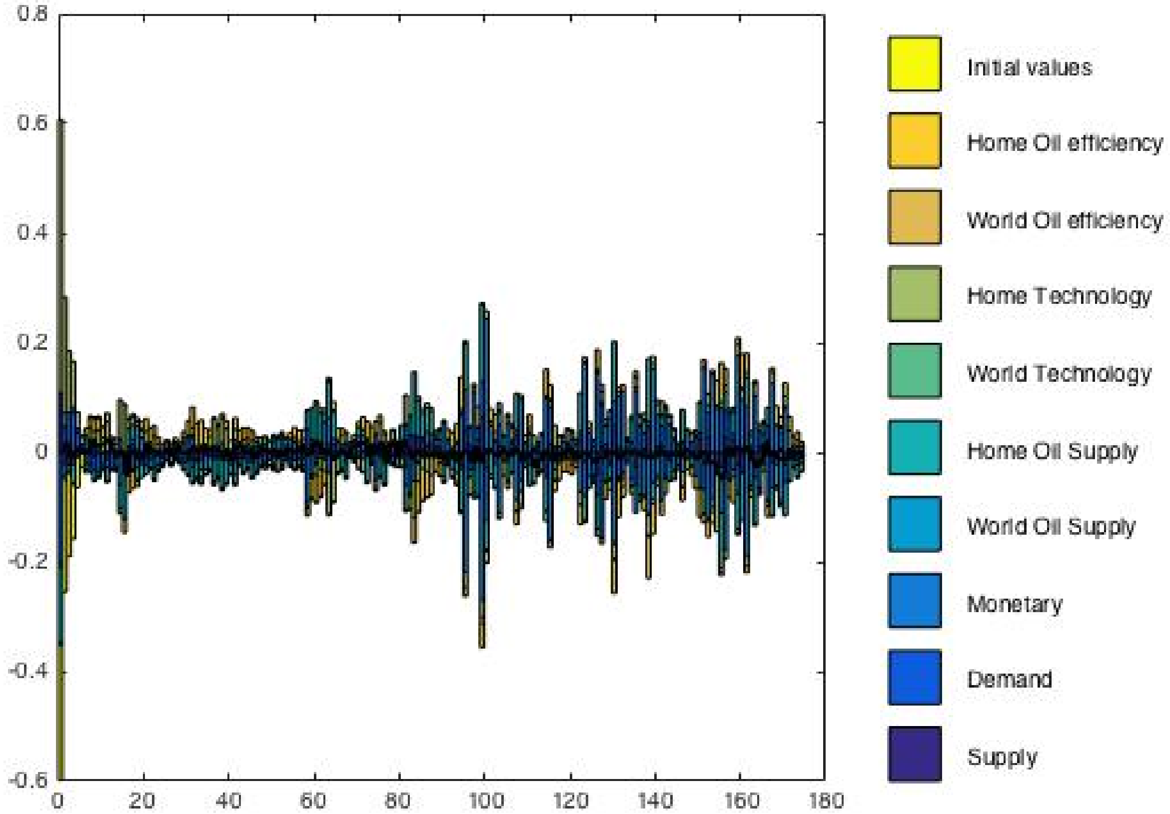

Fig. I.9 Shock decomposition plot of GDP growth in Japan. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the to the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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I.2 Energy Efficiency Analysis

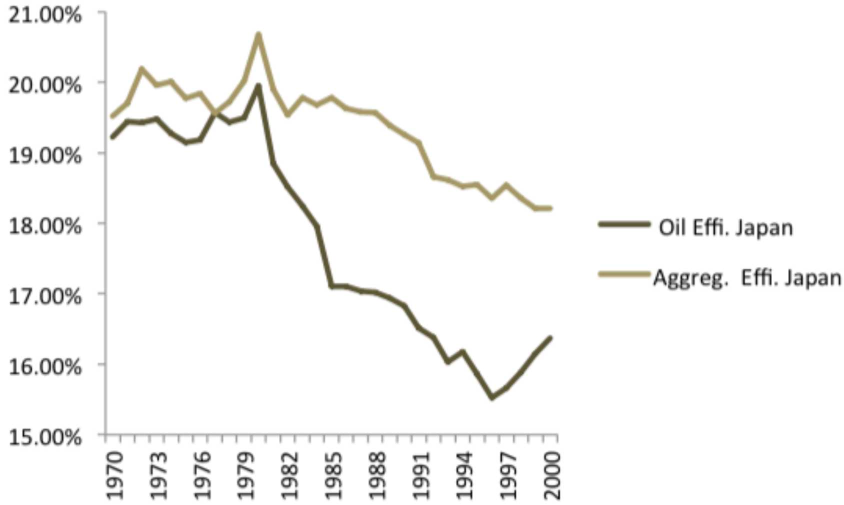

Fig. I.10 Crude oil and petroleum products exergy efficiencies and aggregate exergy efficiencies of the last three decades of the XX century computed for Japan by Warr et al. (2010).

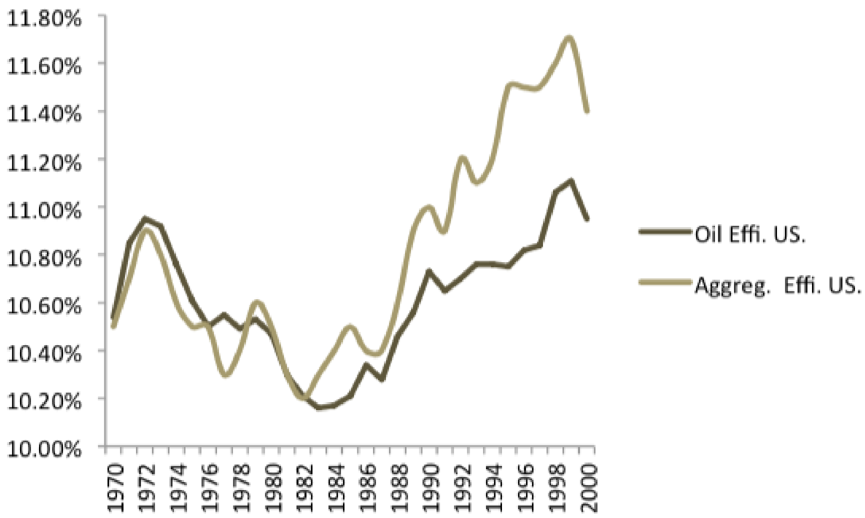

Fig. I.11 Crude oil and petroleum products exergy efficiencies and aggregate exergy efficiencies of the last three decades of the XX century computed for the United States by Warr et al. (2010).

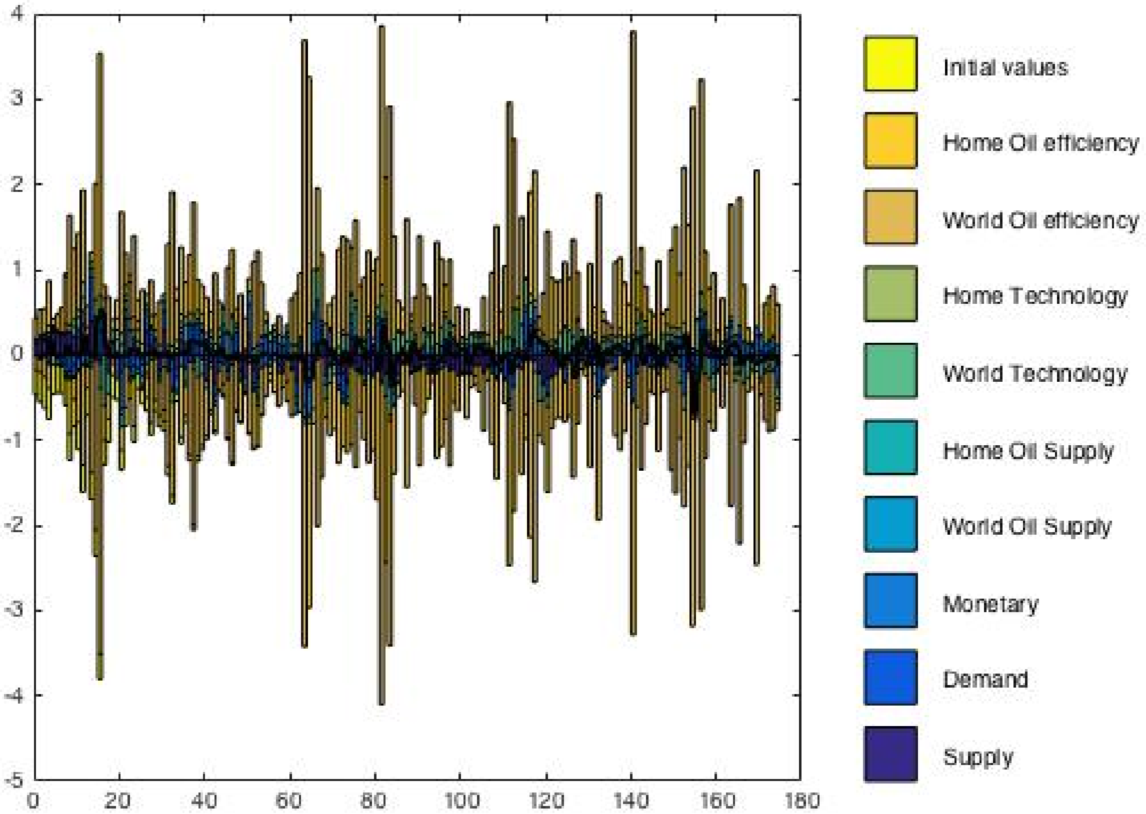

Fig. I.12 Shock decomposition plot of the U.S. oil price. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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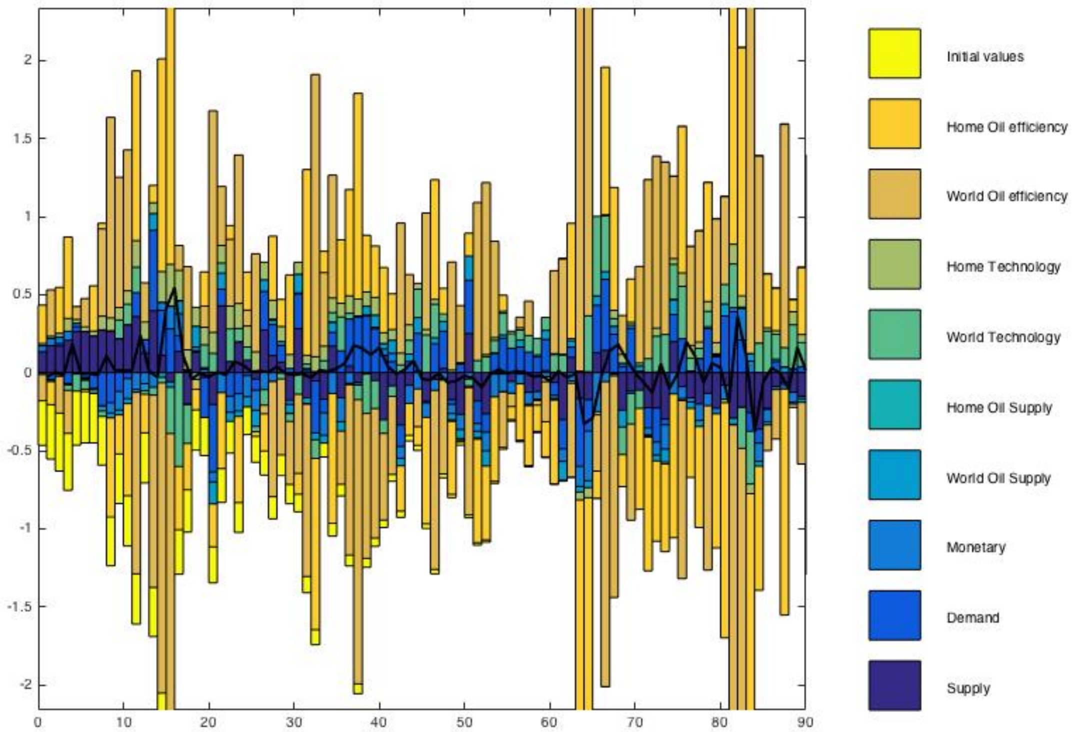

Fig. I.13 Shock decomposition plot of U.S. oil price. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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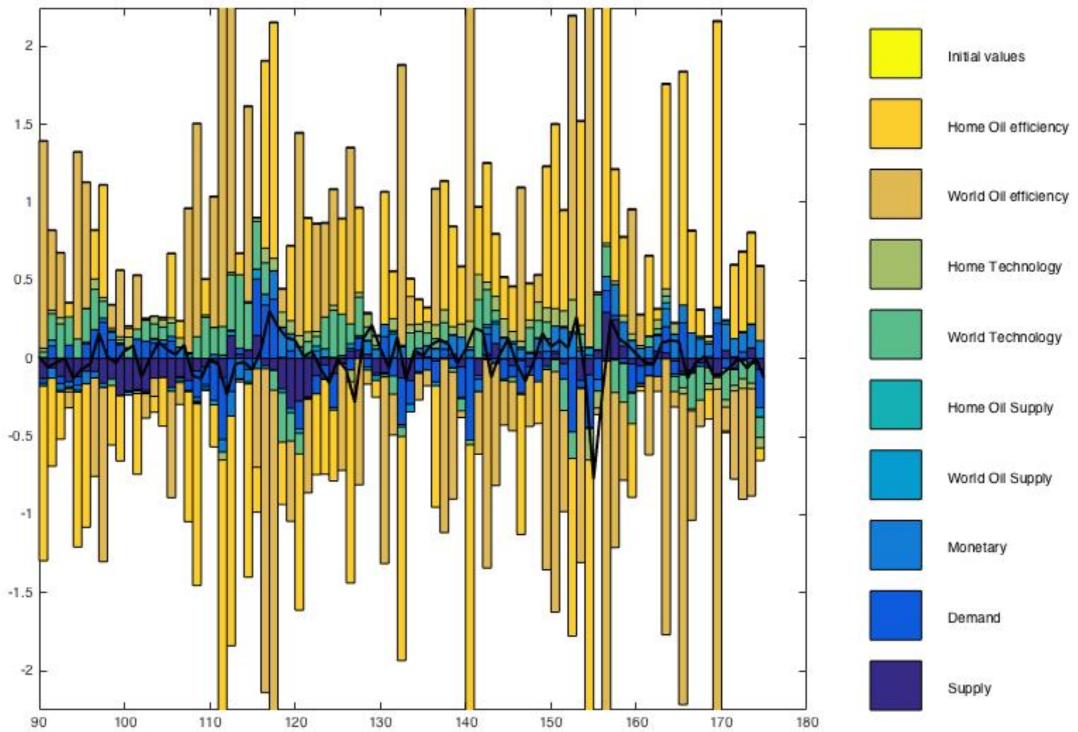

Fig. I.14 Shock decomposition plot of U.S. oil price. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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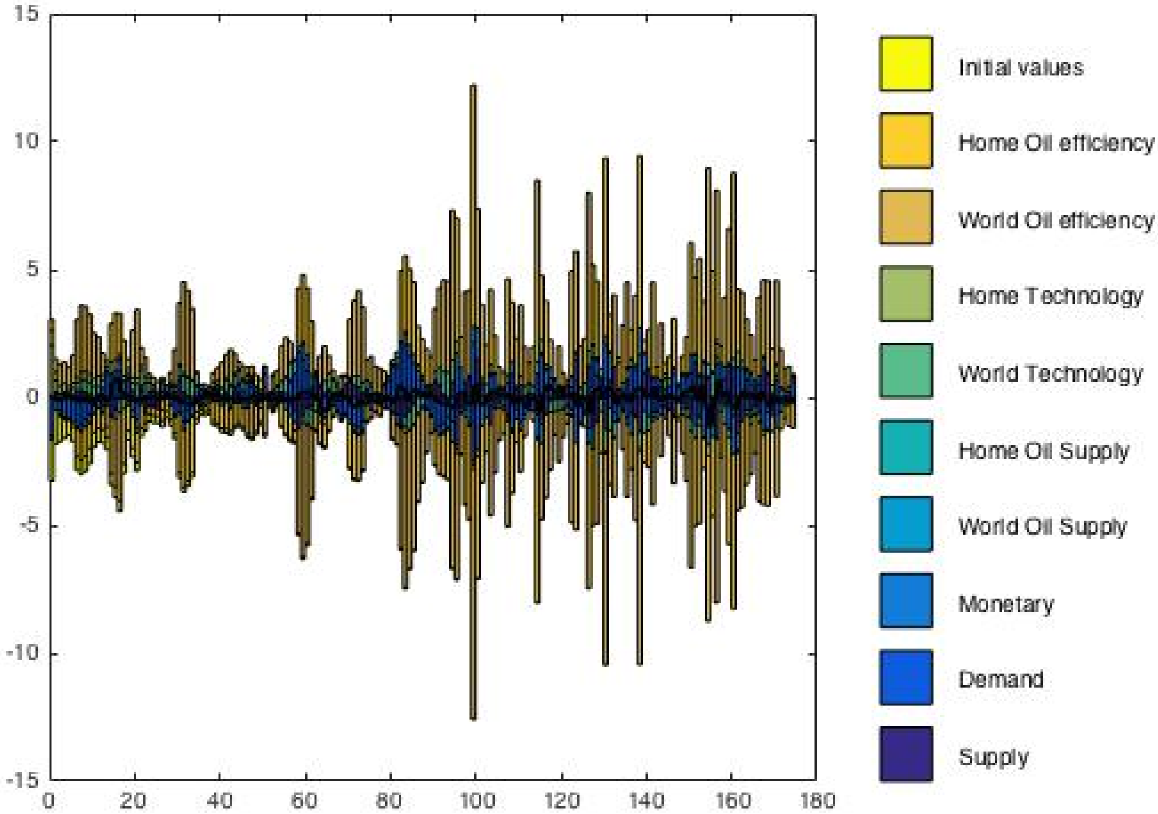

Fig. I.15 Shock decomposition plot of Japan oil price. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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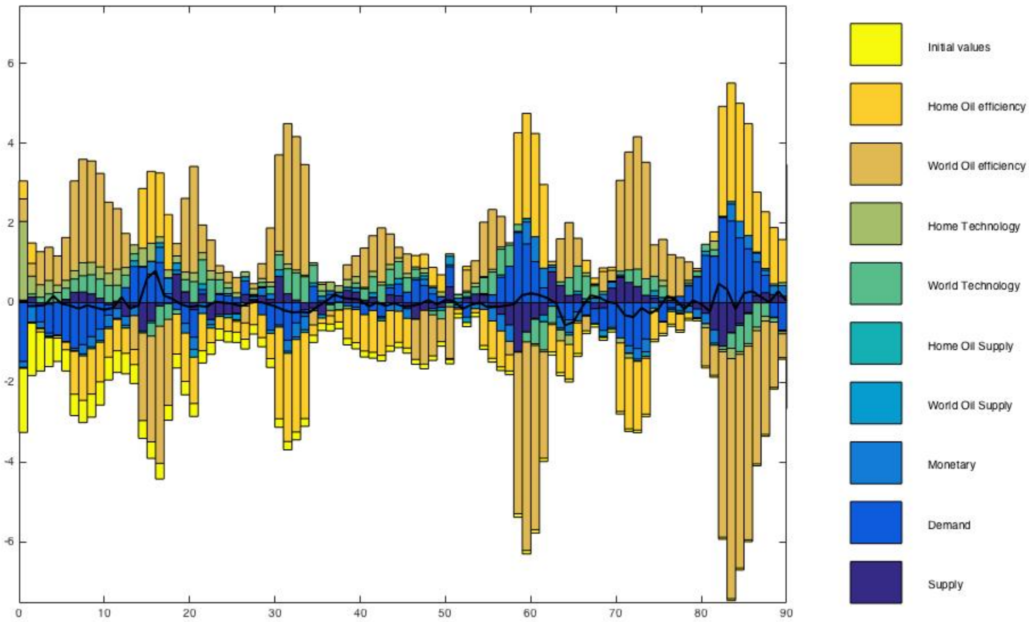

Fig. I.16 Shock decomposition plot of Japan oil price. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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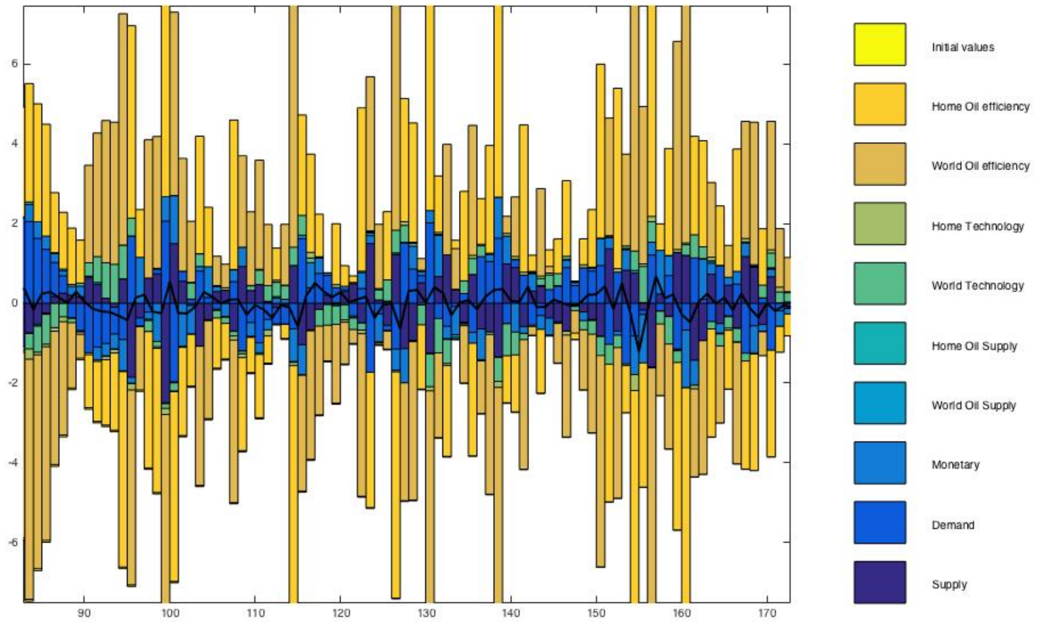

Fig. I.17 Shock decomposition plot of Japan oil price. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified `parameter_ set`. The `parameter_set` is the posterior mode. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state. The x-axis depicts the cumulative number of quarterly periods from 1970 (second quarter) to 2013 (fourth quarter), while the y-axis shows the shocks contribution to percentage deviations from the steady state.

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